A MECHANISM FOR RICHER REPRESENTATION OF VIDEOS FOR CHILDREN:
CALIBRATING CALCULATED ENTROPY TO PERCEIVED ENTROPY

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This study explores the use of the information theory entropy equation in representations of videos for children. The calculated rates of information in the videos are calibrated to the corresponding perceived rates of information as elicited from the twelve 7 to 10 year old girls who were shown video documents. Entropy measures are calculated for several video elements: set time, set incidence, verbal time, verbal incidence, set constraint, nonverbal dependence, and character appearance. As hypothesized, mechanically calculated entropy measure (CEM) was found to be sufficiently similar to perceived entropy measure (PEM) made by children so that they can be used as useful and predictive elements of representations of children’s videos. The relationships between the CEM and the PEM show that CEM could stand for PEM in order to enrich representations for video documents for this age group. Speculations on transferring the CEM to PEM calibration to different age groups and different document types are made, as well as further implications for the field of information science.
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Without the support of my parents, Peter and Bonnie Kearns, this vision could not have been accomplished. With all due respect to Shel Silverstein, this was better than Hurk.
FORWARD

Parts of this research are ethnographic in character. I spent time observing, listening, and talking to children and gathering data that they provided about their own perceptions of selected moving image documents. Occasional use of the first person narrative is a reflection of my personal connection to this work.
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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Children have childlike perspectives on their environment. Children’s materials can be represented with special regard for children’s unique perspectives on their environments. Representation depends as much on codes or grammars as on the things being represented. Young children have not yet learned the grammars of society (Campbell, 1982) that, in an adult world maintain order and keep confusion to a minimum. For example, children have not assimilated the unspoken grammars that dogs should not wear hats or that chicken noodle soup is not a breakfast food. If these simple grammars of the adult world have not yet been imbibed, how is it possible that children will understand adult style representational tactics in a library or other collections of materials intended specifically for their use?

If one casually observes library behaviors in children, even for a few moments, it becomes conspicuously obvious that current library organization tools and schema, such as the Dewey Decimal System or Library of Congress Classification, have very little meaning to children. In fact, children browse organized library collections in the same ways that they browse piles of books in their bedrooms, or groups of books haphazardly thrown into bins for classroom use. Children search until a particular book stands out from the rest to serve a particular information need usually known only to themselves.
Children also use indexes to assist in satisfying a particular need, that is indexes that exist outside the adult library grammars. To understand “index” and its function, one must understand the fundamental meaning of the word. An index is anything that points to something else (O’Connor, 1996), as a map points to one’s desired destination or a phonebook points to the required phone number. In particular, observation of children’s library use indicates that children use book jackets, cover pictures, illustrations, and other children point to what may be relevant information. Visual cues from pictures shown on or in books help children develop quick insights about their usability. More significantly, one notices children using each other as indexes, asking “Did you like this book?” “Where is that book you checked out last week?” or telling a friend “You should read this book. It was so great!”

With a general understanding of some ways children’s library behaviors differ from behaviors of adults in similar environments, I made some observations in an elementary school library which lead to specific inferences of preferred representation of material for children’s collections. These are described in the following case study (Kearns, 2000), summarizing the unintentional consequences of big red dots.

Case Study

The old, unused, out-of-date, and ugly books were weeded from the Easy collection. They were condemned with the mark of a big red dot on the spine (as shown in Figure 1.1), compiled with no regard for standard book organization, and set apart in three columns of shelves between the Hardy Boys series and the collective biographies. These deselected and doomed titles were allotted for first
grade use only because they would not be missed if they were lost, torn, or used as scratch pads. At first I found this shocking.

It was the first day of my school librarian internship and I could only think about the First Graders' freedoms and rights to read, as they had been instilled into my casual thought over the previous two years in library school. There, before me on the First Grade shelves, books were presented in blatant opposition to all I had been taught. It is, after all, the responsibility of the school librarian to "give full meaning to the freedom to read by providing books that enrich the quality and diversity of thought and expression" (ALA & AAP, 1991). First graders were limited to choosing from a group of books, not selected for them as easy readers, but selected for them because they were no longer in good repair to remain part of the regular collection. I was appalled with the notion that my own First Grader was denied enrichment by quality literature because "First Graders have been known to draw in books." We believe, in North America, that "a person's right to use a library should not be denied or abridged because of origin, age, background, or views" (ALA, 1996). The "age" aspect is particularly interesting, since it was incorporated into the existing Library Bill of Rights in 1996 (ALA, 1996). Three years ago these children were granted the right to choose materials in a library, and still they are restricted to borrowing the books with the big red dots. The further I delved into the rights of children in libraries, the more I believed that these children were considered second-class patrons by being subjected to restrictions regarding access to resources (Vandergrift, 1989).
My outrage, though, blinded me to the deeper, if unintentional, function of this crazy, mixed-up First Grade Collection.

**Browsing**

Browsing is a means of accomplishing discovery of an unknown. It consists of an array of processes which involve searching, sampling, and evaluating information objects when a target is not fully articulated (O’Connor, 1993). Young children experience, with regularity, difficulties with expressing their information needs (Kulthau, 1988). Rethinking the organization of a school library collection so that it endorses “creative browsing” (O’Connor, 1988), will help meet the needs of young patrons.

O’Connor’s model for fostering browsing (1988) suggests that creating a browsable facility means simply reconceptualizing the library’s role within the information exchange. The library does present information objects in atypical formats, that is, by not necessarily organizing according to Dewey or Library of Congress organizational models, or—as is usually the case for picture books—alphabetically by authors’ last names. Instead, the library presents information objects –picture books, in this instance—by presenting document attributes to the user. In this way, the responsibility of making intellectual connections to the collection through attributes of individual objects is entrusted to the children themselves. The information seeking process involves children constructing individual meaning to build on their individual experiences while incorporating their own thinking, feeling and discovering (Kulthau, 1994). Whether the target is
recognized by catching “glimpses” (Morse, 1973) of functional information or by perusing a sample of the collection, they key to browsing is that the logical connection is made by the child.

I observed this model in effect. Unintentional, though it may have been, the browsable first grade collection was a context in which children could discover functional (maybe even FUNctional) information.

An Environment for Browsing

The library at this school provides an environment that supports creative browsing with the chaotic organization of its first grade collection. The entire picture book collection is segregated into two areas. The regular easy reader collection is organized alphabetically by authors’ last names and it contains nearly 3000 items. I noticed that children who use this collection (second and third graders) know where to find the “Aurthur” books by Marc Brown, the Dr. Seuss titles, and the “Henry and Mudge” adventures by Cynthia Rylant. Other than these three parts, collection use is minimal. I observed no creative browsing.

The second picture book area is allocated for first grade use only. It consists of three columns with three shelves each, containing a total of less than 150 books. The books have no specified organizational system. Reshelving consists of placing books neatly on shelves that appear to contain fewer books than the others. When children are called to choose a book, they are allowed to browse; in fact, they are encouraged to browse through the shelves until they notice books that appeal to them individually. Some children request specific books, but most information needs are not necessarily being articulated, and each
child manages to leave the library satisfied with his or her serendipitous discovery.

I would suggest creative browsing is successful in this school library because the browsable collection is small; children have time to browse. The attributes that have brought these particular books together in one area, whatever they may be (Age? Dispensability? Size? A big red dot?), have created a working environment for children to seek functional information based on an unarticulated, possibly unknown, information need.

Big Red Dots as Functional Representation of Environment

Browsing, as a visual manipulation of a collection, supports early childhood learners as individual learners. First grade children, in general, display two characteristics that specifically make them candidates for a browsable environment. First, these children are still very visual learners, and secondly, they are egocentric (Kulthau, 1998). Egocentric, visual learners cannot function successfully in an organizational system that assumes every child can search using words and numbers, and that every child has the same, even similar, or even known, information needs. Egocentricity, as a human characteristic, is an asset to a browsing environment that facilitates personal discovery. The child who believes the rest of humanity can visualize life from her perspective will love and will succeed in a library that fosters creative browsing.

The Big Red Dot observation triggered more intrigue about representation issues for children’s media. What aspects of documents could be represented that are not now?
How do children’s (or any users’) abilities and needs impact retrieval design? How can we step away from squeezing children’s materials into existing representation frameworks without loosing any benefits of those frameworks?

Figure 1.1: Big Red Dots shown

From Naïve Science to Scientific Method

While considering basic information needs of children and children’s book collections, I was distracted by two television programs for children that have endured through time. *Sesame Street* and *Mr. Roger’s Neighborhood* (representational still frames shown in Figure 1.2), both having been televised for more than 30 years, communicate messages to child viewers who continue to turn to these programs as basic sources of information. What makes these moving image documents (MID) attractive to child viewers? How might we represent that attractiveness?

My natural human curiosity, often called Naïve Science (Watt and van den Berg, 1995), led me to wonder and to make predictions about the natures of these MIDs and why the communicated messages entice children. Consider just the opening sequences of both programs as pieces of two separate messages that essentially communicate the same or similar information (i.e. introductions to children’s television programming).
Figure 1.2: Representational Still frames from *Sesame Street* and *Mr. Roger’s Neighborhood*.

After viewing each opening sequence, one notices attributes in both that are very different, seemingly opposite. Such attributes as pace, locations, number of scene changes, number of characters, color distribution, and camera angles obviously differ between the two documents. Closer analysis of one of these attributes, scene changes, as shown in Table 1.1, led to some interesting implications. The analysis is a result of my own informal calculations and observations when then MIDs were viewed in video editing software at one second intervals.

<table>
<thead>
<tr>
<th></th>
<th>Mr. Rogers’ Neighborhood</th>
<th>Sesame Street</th>
</tr>
</thead>
<tbody>
<tr>
<td>length of clip</td>
<td>83 seconds</td>
<td>58 seconds</td>
</tr>
<tr>
<td>number of background scene changes</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>average seconds per scene change</td>
<td>27.7</td>
<td>1.8</td>
</tr>
<tr>
<td>average frames per scene change</td>
<td>831</td>
<td>54</td>
</tr>
<tr>
<td>interest level</td>
<td>low</td>
<td>high</td>
</tr>
</tbody>
</table>

Table 1.1: Calculated differences in the rate of information in *Sesame Street* and *Mr. Roger’s Neighborhood*. 
The *Sesame Street* introduction is 58 seconds. Background scene changes occur 31 times at an average of 1.8 seconds per scene change. At 30 frames per second, the average number of frames between scene changes is 54. I personally perceived this clip to be highly interesting. In the 83 seconds of the introduction to *Mr. Rogers’ Neighborhood*, background scene changes occur at 20 seconds, 28 seconds, and at 32 seconds. On average, background scene changes occur every 27.7 seconds. At 30 frames per second, the average number of frames between scene changes is 831. I was personally less interested in this clip than in the first.

For a more rigorous analysis of each MID, the clips were run through Virage® Video Logger video analysis software with analysis sensitivity set at various levels (see [http://www.virage.com/products/videologger.html](http://www.virage.com/products/videologger.html)) (sensitivity window shown in Figure 1.3). The software selects keyframes (as in Figure 1.4) based on physical attributes of the video data stream.

![Figure 1.3: Virage Video Logger sensitivity window](image)
Figure 1.4: Virage Video Logger grabbing frames

With sensitivities (size of discontinuity in the video data stream required to trigger selection) set at levels 20 and 50 (on a scale of 0 to 100) for each MID, one notices that—though the actual numbers are different—the relative numbers of keyframes extracted bear relationships similar to the background scene change numbers that were made during my informal analysis. Figures 1.5 through 1.8 demonstrate selected key frames at various sensitivities.
Original calculations had shown the ratio of rates of information to be about 1:10 for *Mr. Roger’s Neighborhood* and *Sesame Street*. Set at sensitivity level 20, the *Virage* software elicited a ratio of about 1:4; and set at sensitivity level 50, about 1:3. The *Virage* relationships show that the segments have similar relationships to those in the background scene changes, specifically many fewer in *Mr. Roger’s Neighborhood* than in *Sesame Street*. 
Figure 1.6: *Sesame Street* segment set at sensitivity level 20.
Figure 1.7: *Mr. Roger's Neighborhood* sequences set at sensitivity level 50.
Is there a link or some relationship between the rate of information and the viewer’s self-proclaimed interest level in MIDs? Would this have any relation to children and representing children's materials, since information can be seen as “that which adds to a representation” (Moles, p. 19)? These questions drove me toward examination of these ideas through systematic controlled inquiry and informed speculation, as detailed in the following chapters.

Understanding Communication Theory

In order to establish a foundation for examining these questions, I looked to Shannon and Weaver’s *The Mathematical Theory of Communication* (1949). To make use of the model, one must understand *communication* and *information*, which cannot be separated from *entropy*. Shannon specified a semantic problem in communication and Weaver articulated this semantic problem through the question *How precisely do the
transmitted symbols convey the desired meaning? This is the problem in the common use of the definition of entropy: desired meaning changes through the disciplines.

Variations on the definitions appear to be influenced by the specific discipline the definition serves. Campbell (1982) combines the philosophies of biology and information to assert

“Biologists as well as philosophers have suggested that the universe, and the living forms it contains, are based on chance, but not on accident. To put it another way, forces of chance and of antichance coexist in a complementary relationship. The random element is called entropy, the agent of chaos, which tends to mix up the unmixed, to destroy meaning. The nonrandom element is information, which exploits the uncertainty inherent in the entropy principle to generate new structures, to inform the world in novel ways” (p. 11).

Prata’s (1992) definition shows us the roots of entropy in thermodynamics.

“One of the fundamental laws of nature is that entropy never decreases and that it usually increases. Entropy often is described as a measure of disorder, so the law of entropy (AKA the Second Law of Thermodynamics) suggests that nature tends toward greater disorder. (There is a more precise mathematical definition of entropy, but disorder serves us well enough)” (p. 10).

In the web dictionary of cybernetics and systems of Principia Cybernetica, (http://pespmc1.vub.ac.be/ASC/INDEXASC.html) (Turchin, Joslyn, Heylighen, & Bollen, 1999) entropy is defined as unavailable energy or molecular disorder, and readers are warned that entropy itself should not be confused with uncertainty. This source also
defines information as the difference “between two states of uncertainty before and after a message has been received.” However, Communication Theory is clearly about entropy as it is related to uncertainty, and information, as defined above, where entropy in a communication is a measure of one’s freedom of choice when one selects a message (Weaver, 1949). In short, entropy is the “average rate of information in a communicated message” (OED).

In similar fashion, information has also been variously defined and, at times, misconstrued. Information cannot be confused with meaning, nor can it be used interchangeably, as is demonstrated in Wilson’s definition of information as “Anything I can forget” (personal communication, Brian O’Connor, 1999) and in Shannon’s definition, “The semantic aspects of communication are irrelevant to the engineering aspects” (1949, p. 3). Weaver adds that in Shannon’s Communication Theory the word information relates “not so much to what you do say, as to what you could say.” (p. 100). This notion is exactly what is meant in Weaver’s definition. Uncertainty is information is entropy. Shannon also claims that one message of pure nonsense and one message loaded with meaning can be exactly equivalent in this communication theory. Moles complies, asserting that “information differs essentially from meaning: information is only a measure of complexity” (1966, p. 196).

At this point, a closer examination of Shannon’s theory is in order. As he envisioned it for Bell Laboratories in 1949, communication is represented in a simple diagram, shown in Figure 1.9.
Figure 1.9: Messages are communicated through a standard system represented in Shannon’s diagram (1949).

The information source sends a message to a transmitter where the message becomes a signal. The signal is sent through a communication channel and is received by a receiver. The receiver converts the signal back into a message before it is sent on to the destination. This process holds for any communication.

Since entropy is a measure of rate of information communicated in a message, Shannon expresses entropy as an equation, Figure 1.10.

\[ H = -\sum p_i \log p_i \]

- \( H \) = entropy/information
- \( p \) = probability of choice of \( i \)
- \( i \) = set of independent symbols

Figure 1.10: Shannon’s basic entropy (H) equation (1949).
Weaver explains this equation thus: information is measured by the logarithm of the number of available choices when selecting a message. Entropy is a measure of the degree of randomness. When one is completely free from bias in choice (when 2 ps in the equation are equal) entropy (H), or information, is highest.

In defense of this communication theory, Weaver asserts that information being “measured by entropy is, after all, natural when we remember that information, in communication theory, is associated with the amount of freedom of choice we have in constructing messages” (p. 103).

Shannon’s model of communication provoked other researchers to acknowledge its application to telephone systems, as Shannon had developed while he worked with Bell Laboratories, but to question its connection to people. “Information theory was primarily directed toward the physical transmission of signals and, as such, its limitation was recognized with regard to overall complexities of human communication” (Goffman, 1970, p. 724). Hayes (1991) also questions, Can the entropy measure provide means for recognizing both the statistical issues involved in efficient transmission AND the importance of the signal to the recipient of it? In response he adds a human factor to the Shannon model by building on what Shannon accomplished. Hayes defines information as “any stimulus that alters cognitive structure in the receiver” (p. 3) In accordance with these definitions, he inserts the importance to the recipient into Shannon’s equation with new factor, r (given in Figure 1.11).
This measure assigns to each signal, \( x_i \), another function that measures the importance to the recipient. In Hayes’ equation (Figure 1.12), \( r \) can equal relevance in terms of retrieval system evaluation. The new equation results in a new entropy called *weighted entropy*, which does indeed claim to recognize the significance of the signal to the receiver without discrediting the statistical issues involved in message transmission.

Hayes draws attention to the concept *verifiable truth* that the term *communication* has come to mean, through colloquial use, as ambiguous as the term *information*. He calls communication the *vehicle of information* (p. 4). Weaver is somewhat less abstract. He asserts communication is comprised of all of the procedures by which *one mind may affect another*. If this is true, then Shannon’s original model, in fact, does involve a human element. Examples that Weaver provides include music, dance, theatre, still and moving pictures, and all human behavior. Watt (1979), O’Connor (1991), and Augst &
O’Connor (1999) model moving image documents in a manner founded on Shannon and Weaver.

Consider one more interpretation of entropy. Watt brings entropy into daily American perspective with his definition.

“Information theory statistics are called entropies and they measure the degree of randomness or unpredictability in a set of elements. These elements can be letters, numbers, words, [television] program production elements, or any other well-defined unit of measurement. The higher the information theory entropy, the less predictable is the appearance of any unit, and the more complex is the message” (p. 59).

Watt provides a segue back into the original discussion about rate of change of information in children’s television programming.

Entropy in Moving Image Documents

Augst & O’Connor (1999) recognize discontinuities in moving image documents, that represent an unpredictability in the data stream. This “precarious balance between stillness and movement” (p. 360) causes viewers’ opinions of two moving image documents communicating the same information (in their case, 48 women running 26 miles in urban settings) to differ significantly. Document A is described by most test viewers as dynamic, exciting, engaging and Document B is described as dull and boring. In this study, the responses that were elicited from viewers were similar to anecdotal data from the opening segments of Sesame Street and Mr. Rogers’ Neighborhood. It is in the discontinuities that viewers notice change. Change in visual fields, as Watt (1978)
asserts, is related to higher viewer attention. Greater viewer attention coincides with a
greater element of surprise, greater information, and greater entropy.

Dancing With Entropy

Hayes’ definition of understanding involves recognition of information,
comparison of content, and integration into existing knowledge. Understanding is
achieved through communication. Comm- indicates togetherness but simultaneity is not
implied. As Hayes indicates, it is not the simple flip-flopping of A to B, B to A, A to B.
The originator of the message assumes some knowledge of the anticipated receiver, as in
an intended audience. On a simple level, the sender (perhaps a stand up comedian)
assumes that the recipient (the audience) speaks the same language and shares similar life
experiences at the time of the delivery of the joke. On another level, the sender (say,
Shakespeare) assumes that his audience speaks the same language of the verse in his
sonnet, shares a common interest in poetry, and understands from what culture and
perspective the piece was written. The original audience could dance without lessons; a
10th grader in 1999 needs lessons in sonnets, allusion, metaphor. I never met the Bard, but
we can communicate.

Each partner knows something about the other. They share the common interest
of dancing; they are standing in a room facing each other; they may both know how to
waltz despite never having waltzed together. The same is true of information.

Communication suggests that knowledge of one another (or by one partner when the
other is temporally unavailable) is necessary in order to reduce entropy. Feedback adjusts
the assumptions. These steps we dance with entropy are information. The dance is
communication.
What does this have to do with representing children’s materials? Appropriate and functional representation depends on knowledgeable partners. Marr (1982) asserts representation is a system for highlighting certain characteristics of an entity together with an explanation of the code for doing this. The user of the representation has to know the code. Thus, designing representation of children’s materials ought to speak to the elements that are important to children in ways that make sense to them (or those who might make selections on their behalf).

Representation, Aboutness, and Moving Image Documents

Richer representation of documents leads to greater efficacy in information retrieval. Many attributes of different media must be considered in representation in order to facilitate successful retrieval of those documents in a collection. For example, important attributes examined in representing adult’s books may not be important in representing children’s books, and those for children’s books are likely not ideal for full representations of images: every audience requires specific and egocentric representation of each medium. This notion introduces what Hayes (1993) wrote about representation. Facts (statements whose truth is verifiable) are representations derived from the real world, or from the information object. Data (recorded symbols) represent the facts. What one discovers about an MID is providing facts about its reality, what it is. How one expresses the facts—words, keyframes, calculated measurements—is the data about the representation. And this must be done in such a way as to enable the user to make the same assumptions about the representation that they would make given the original (Goodrum, 2001).
To understand representation in the realm of information science, one must first understand aboutness, since representative data must explain what the real object is about. Knowing about the object is the way to assign something else to “stand for” (O’Connor, 1996, 11) the original. We can present Figure 1.13 and ask, “What is it?” A common answer might be, “It is a dog.” This is incorrect, as it is not a dog but a representation of a dog. The original object is about “dog;” the digital image is the data about the facts, a representation of dog. Likewise, with a second glance at Figure 1.14, one sees that it is not a dog but another representation of “dog” and, as is the intent of the artist, a representation of first representation (the digital image) dog. Aboutness, in this case “dog”, has not changed through the degrees of representation.

Aboutness is not merely describing an object, but developing a functional representation of the object. This fundamental concept seems to be lost in the operational definitions of various information retrieval models (Bruza, Song, & Wong, 2000). The objective here is to promote the basic definition as it relates to functionality for the user, not as it serves a specific retrieval system. The one who assigns value to aboutness, is the one for whom the representation is functional. This means that the person who created a
record in a collection for a particular item, say a child’s book, may well have developed a functional representation for himself or herself, and not necessarily for the child user whose functional representation may be as simple as “it has a blue cover.”

The probability of user satisfaction is a function of the document’s appropriate representation of aboutness (Maron, 1977), but this may well be unknowable. Cooper (1971) explains how the importance of specific representative descriptors will be weighted differently by different users. Wilson (1973) terms this phenomenon “situational relevance”—what is relevant to one person in one situation is not necessarily relevant to another person in a similar situation. In addition, a representation can be user-centered only if the creator can understand aboutness from the perception of the intended user (Wilson, 1968), and exhausts all perceptions of all possible users. If it were conceivable to clearly understand aboutness from a user’s perspective, the magnitude of the representation to include all possible (or even likely) perceptions could cause one person to spend many lifetimes representing a single object.

Creating surrogates is like repeating the dance with entropy: the creator assumes to know something about the user and the user about the creator. Without the assumed knowledge of the other, information retrieval cannot be a channel of communication (Blair, 1990). As demonstrated in following chapters, this project attempts to operationalize this idea by matching the users’ perceptions of the rate of change of information into calculated measurements, and proposing one method for creating calculable representations of users’ perceptions for the purpose of richer representation of MIDs for children audiences.
Recent research endeavored to build knowledge about moving image documents and how their realities and aboutness may be represented, or surrogates be assigned, in ways appropriate to this format, particularly with regard to extra-topical attributes such as time and movement (Goodrum, 1997). Some of the first research in this area implores surrogate creators to design “book-like” intellectual and physical access to MIDs (O’Connor, 1985); that is, to make access to MIDs as functional and simple as access to books. Though this basic idea of MID representation does indeed provide practical access to whole documents by means of reducing long lengths of film or video to short surrogates, the notion of “book-like” access can be misconstrued to mean MID representations should use the same representational methods applied to print linguistic materials. Book-like access actually implies the user’s ease of access: maintain ease of use of the retrieval systems no matter the document type.

A significant problem with visual information retrieval is that the lack of representational congruency is magnified by the “utilization of text for visually directed information needs” (Goodrum, 1997, p.17). If film or video documents are represented solely with printed words, the representation is not likely to enable the user to make competent assumptions about the original work. Pictures are not words and there is no simple algorithmic relationship between pictures and words (such as 1 picture=1000 words). Speculations about keyframe, image, and moving image surrogates have recently increased in the literature, as image documents have become more numerous (see Rorvig, 1993). The surrogate is intended to stand for the full document for the purpose of increasing browseability of the original and providing a means for more timely relevance judgements of the user (O’Connor, 1984). Examining MIDs at different “levels of
penetration” (O’Connor, 1984, p. 179) can reduce user search time and evaluation time. Examining children’s perceptions of video documents aims at developing one more level of penetration that works to incorporate user perception into the representation.
CHAPTER 2

DEVELOPING CONCEPTS AND A PROBLEM STATEMENT

How might we use a mechanically derived measure to predict children’s engagements with videos? Could we establish a connection between some group of children’s verbalized perceptions of MIDs with some calculable measurement of the document?

Predicting document aboutness is a primary task of one who creates a representation of a document for retrieval, and it is fundamental to effective document retrieval (Maron, 1977). An aboutness prediction is not likely to be effective if it is merely a simple summary of content, since document meaning and utility depends as much on the recipient as on the message sent (Hayes, 1994); since form aspects, such as how aboutness is presented, degree of organization, timeliness are significant (Robertson, Maron, & Cooper, 1982); and since the code must be known to the seeker. The document creator (the book author, the screenplay writer, the photographer, and so on) may seem to be the best predictor of aboutness: it is, after all, by his or her own perception of topic aboutness that the document was created. But can an author foresee all possible uses of his work? Did William Shakespeare know, when he composed Hamlet, that school children in the 21st Century would be reading his play and receiving passing or failing grades based on their own interpretations? Or that a group of teenagers in 1986 would combine the play—a tragedy—with the wit of Theodore Geisel and create a comedic
video called Green Eggs and Hamlet? Or that my daughter would sit on his collective works so that she could sit up higher at her grandmother’s dinner table? Methinks not. Similarly, aboutness is not merely a function of topicality; it is also a function of document form (Augst & O’Connor, 1999).

Aboutness

The document creator cannot know at the moment of creation every possible information need his or her document could satisfy in its lifetime, any more than the publisher can, or the reader, or the photographer, or the indexer, so they alone cannot determine symbionic aboutness, though each might be able to state some sort of primary aboutness. The intended meaning or utility for the audience “for whom I made this work”—presumably an author—knows Hayes’ r for the original audience. Together they could produce a rich representation. Collaboration between all users is improbable for every document that exists—when one considers user time and quantity and document supply and availability—so we have grown to accept the representation generated by one person, such as the indexer, the cataloguer, or the artist. If one person is expected to create a surrogate, or a “sum of attributes” (Arnheim, 1969, p.173), that satisfies the minimal information required for effective document retrieval for all possible users, then this person should view the document from various angles. O’Connor and O’Connor (1998) call this set of angles a “representation palette” with which the responsible person holds in mind an image of all possible users’ profiles to determine the depth of representation, or “levels of penetration” (O’Connor, 1984, p. 179), the indexer has chosen to engage. One would expect the palette of attributes to include all the obvious diachronic elements (author and title, for a book; creator and medium, for a painting) and
to include user-specific elements that may not apply to all documents beyond the smaller group with a particular purpose. For example, the representation palette for moving image documents for children might include age-specific topic information, such as content description in the words of children in that age group, as well as a form measurement such as the calculated amount of surprise the moving image document contains—its entropy. If a document’s entropy could be assigned a value, predicting how it would be perceived by children, the representation palette could hold one more color, with the intent of painting a more complete picture.

There is a somewhat paradoxical relationship between an original document and the surrogate. Representation implies a loss of some information (O’Connor & O’Connor, 1998) and this loss can be seen as a strength for the representation because less information through which to sort means less search time spent on retrieval. On the other hand, complete representations could become greater than the original if the surrogate were to contain all relevant representational information for all possible users in all possible situations. Not only is there a loss of information from the original, but also there is an accumulation of information describing the aboutness of the original. So how does the indexer begin to both reduce information and include all possible descriptions of a document for a representation? As forms change over time, today’s measure might have different implications for future users, yet the basic relation should hold—more surprise yields more interest, with other aspects being equal.

Wilson (1968) asserts that unless the indexer shares specific physiological and intellectual experiences with the user, the surrogate will likely be ineffective. He asserts,
“Unless, then, indexing is done specifically for me, and on the basis of intimate knowledge of my interests and requirements, it is likely that I shall always have to engage in exploration, in searching, for the things that are most important to me” (p. 101).

Instead of attempting to read the minds of individual children in order to personalize aboutness, this study attempts to establish a connection between some children’s verbalized perceptions of entropy in moving image documents with an established calculable measurement for quantifying entropy. That is, to establish a measure for a shared physiological experience. If such a connection could be established, indexers would not need to assume to understand physical and intellectual circumstances of every child viewer.

If no equation existed to determine the rate of information in a message, receptor perception would be the only determinant of the rate of information in a message. Moles (1966) claims that not only is the rate of information determined by the structures that the receptor perceives in the message, but also that these structures are created, or recognized, because of the culmination of memories, past experiences, and the organization and grammars of the messages in which these structures have already appeared. User groups with different experiences, then, might well perceive rates of information in a message very differently. Children, for example—because they have not yet necessarily accepted the life rules that dogs should not wear hats or that chicken noodle soup is not a breakfast food—might have age-specific perceptions of messages dependent upon levels of development and cognition, whether the message is intended for adult or child receptors. If children have different experiences than adults, and they
perceive rates of information differently, then it would seem reasonable that their
document aboutness (form aboutness and content aboutness) should be represented in
ways that are also different.

Relevance

Recall Hayes’ \( r \) value (1993), as described in Chapter 1. It adds an element of
significance of the communicated signal to the user or the recipient of the signal in
Shannon’s model. The \( r \) variable is seen as a measure of relevance added to an equation
that was originally designed to measure communication through a telephonic system.
Moles (1966) concurs that information theory is usually presented with a “dogmatic
rigidity” (p. 56) rendering it unmistakably insufficient when one attempts to apply it to a
human recipient. So that the theory can be applied to human receptors, an element of
relevance is added.

A lack of \( r \) indicates a lack of meaning (Schamber 1994). Whatever information
solves the particular problem at a particular moment for a particular individual is relevant
for that person in that situation. Patrick Wilson (1973) describes situational relevance as
precisely this; that which resolves “costly ignorance” not only because it is “on topic,”
but also because it is conceptually, critically, and linguistically appropriate (Wilson,
1977). This could mean, then, that a cup of coffee is relevant. (All who have experienced
a throbbing caffeine headache might well attest to its relevance.) If the cup of coffee does
not solve the problem (get rid of the headache) then the search for more information, or
relevance, continues. Perhaps relevance is not achieved until the searcher finds some
acetaminophen tablets or a quiet, dark place to grab a nap.
Essentially, in use, relevance can mean whatever the searcher requires it to mean. “Bearing upon the matter at hand,” from the Oxford English Dictionary, demonstrates that whoever is concerned with the matter, or the problem, determines relevance. When determining what is relevant for an individual, consider the following taxonomic statement. Relevance is “what will answer the question…what may suggest a way of answering the question…[or] what will help one formulate what may turn out to be the answer one seeks” (Wilson, 1968, p. 48). If the question is what’s for supper? then relevance may be acquired by respectively the following: “Pizza;” “I’m not sure, let me call my mom;” or “Let’s order out.”

Replace the basic need of food—or coffee—with an information need. The meaning of relevance remains the same. It is a “relation between a document and a person, relative to a given search for information” (Robertson, Maron, & Cooper, 1982). Relevance, or lack of relevance, could restrict the meaning or utility of the surrogate for a user. The representation should be created with an informed regard specifically for the user group for which the representation is intended. The representation is a message in its own right.

Hayes’ $r$, then, could stand, at least in part, for the physiological and emotional aspects of decoding ability for any user. Hayes’ $r$ is similar to the O’Connor and O’Connor palette. Again, the palette has topical and extra-topical components—everyone experiences essentially the same stimulus set from a particular document, but the individual palette yields a potentially different interpretation. Each individual’s palette yields how emotional the individual museum goer felt after visiting the Van Gogh exhibit, or a measure of frustration Sophomore English students felt during their first
reading of Chaucer’s *The Canterbury Tales*. In the case of perceptions of rates of information in a message, \( r \) could be an entropy value. What matters here is that Shannon’s entropy equation has been weighted in order to express significance, or personalization, for a particular receptor for a particular message. Maron (1977) suggests that relevance is based on topical and extratopical elements, such as document timeliness, reading level, or interest level. Entropy is simply one more of these extratopical elements.

If the message is a moving image document and the receptor is a 9-year-old child, the same ideas apply. Moving image documents—a film, a video, a television program, a DVD—over time involve both visual and auditory stimulation of the user in order to invoke user perception. Thus, they are well suited to description, in part, by entropy measures. While the degree of surprise of a document’s topic might be difficult to predict, the rate of change in the physical data stream is not.

Integrated Perception

Since Shannon’s information theory was concerned with inanimate communications systems, when applied to a human receptor, the problem really lies with receptor perception (Moles, 1966). When the transmitted signal is a moving image document, what basic unit is the receptor perceiving? The basic unit could be the single frame (ordinarily at the rate of 30 per second) or, smaller yet, the pixel (picture element). However, without freezing the data stream or enlarging the digital video image, human perception of the single frame or the single pixel is, at best, very difficult. Instead, we perceive the message as a group, or bundle, of all the smaller units. This “Signal Bundle Model” (O’Connor, 1991), shown in Figure 2.1, assumes the viewer perceives the stream of data over time without consciously examining the individual frame or pixel. Viewers
assume an integral, rather than an aggregate, viewpoint of the document, as in Gestalt theory, where a group of elements is perceived as a whole unit and not as a result of randomly occurring events, or attributes. Some researchers use the individual pixel as a basic unit of measure. This is the case with information retrieval system designers whose main concern is the system (see Zachary, 2000). At the human level, however, the single pixel is indecipherable from the bundle.

Figure 2.1: Signal Bundle Model; adapted from O’Connor 1991.

Gestalt theory expresses a means for someone to identify something without being able to, or being expected to, identify any particular individual characteristic that defines it. Humans naturally organize and categorize what they perceive (Roth & Frisbey, 1986). In one sense, we categorize like stimuli over time as “the same” and pay particular attention to “what’s different” based on some generic criteria in the object (Fischler & Firschein, 1987). Some stimuli involve higher processing of a collection of neurons
forming nerve paths. Even the pain response (something comparatively simple), explains Comparative Physiologist Brian Bagatto, involves many thousands of neurons sensing pain (say, at the hand on a stove), transforming the signal into a set of electrical depolarization events for transport to the brain. The brain interprets the signal and integrates the collective response to the muscular system to pull the hand away. So one can imagine how much more complex the process becomes for looking at a picture, transporting what has been captured by the optic nerve to the appropriate regions of the brain—and more complex yet, the addition of an auditory element for a moving image document (B. Bagatto, personal communication, April 2001). “Most noteworthy is the awesome complexity of the cognitive processes that must be performed in order to make adequate perception possible” (Arnheim, 1967, p. 40). The physiology of a “glance” (Macbeth, 1999) is more complex than a camera capturing a frame, because vision is an activity of the brain (Arnheim, 1967) and not merely an activity of data entry.

Form Complexity

For moving image documents, Moles (1966) calls the Gestalt “form.” Form complexity, according to Watt (1979), is the perceived degree of randomness of form attributes that causes a viewer to attain “optimal level[s] of sensory stimulation” (p. 68). Watt & Krull (1974) and Krull, Watt, & Lichty (1977) tested viewer perception of this degree of randomness of form attributes (entropy) in a set of television programs. The 1974 study attempted to assign a value, termed dynufam, to 58 television programs. Dynufam is comprised of two values: dynamics and unfamiliarity. Dynamics is linked to activity in the actual data stream of the program, such as the randomness of the set appearances and the number of verbalization characters make. Unfamiliarity is related to
amount of randomness or unpredictability in the program message. These combined scores were compared to adolescent viewers’ self-reported aggressive viewing behaviors. From these comparisons, Watt and Krull concluded that dynufam is a “useful measure of program form with a superior ability to measure nonrandom viewing patterns” (p. 65).

In a second study, Krull, Watt, & Lichty (1977) compared the relationship between form as a predictor of viewing and viewer preference for particular programs, with the objective of finding a method of measurement to express aspects of program form that are “important to viewers” (p. 830). These studies established a predictive link between television form attributes and viewers’ behavioral concepts. Form complexity in these studies was determined by a set of equations derived from the original blueprint of Shannon’s entropy equation. In a subsequent study, Watt (1979) described the equations used to determine entropy in light of both form attributes (shown in Figure 2.2) and content attributes, noting form and content complexity must be regarded integrally when evaluating and generalizing viewer behaviors. Watt asserts that these measurements are predictors of viewer attention, viewer arousal, viewer behavior, and the viewer’s decision to watch the same program next time it airs. Form complexity generally will not outweigh content in determining viewer interest in a program. Recall the examples of *Sesame Street* and *Mr. Roger’s Neighborhood* from Chapter 1. *Sesame Street* has a greater calculated form complexity than *Mr. Roger’s Neighborhood*, and yet both programs have endured over time. Form complexity is not the only component of a child’s *r* palette, but it is a significant component and therefore study of form alone is significant.
Form attributes, *entropies*, can be a determinant of a viewer’s decision to select a particular program to watch (Watt, 1979). Higher entropy (recall the OED definition: the rate of communication in a message) in a program can be equated with the amount of surprise in the message, or the unpredictability of the message. To modernize Watt’s findings, this could be one reason why so many people choose to watch *ER* every Thursday evening, and why fewer choose to watch an orchestra performing on PBS; that is, program preference is at least partially due to a viewer’s response to the complexity of form attributes. It is important to note also that some age groups, like the very young and older adults, seem to prefer the more predictable programming (Watt, 1979).
Perception: Child Viewers and MIDs

Moving image documents are distinguished from other types of communications media largely by form, rather than content (Huston & Wright, 1983). Viewers are subjected to both visual and auditory information over time in MIDs (see Figure 2.1). How children perceive MIDs seems to be directly related to attention and comprehension of the document shown (Watt & Welch, 1983). Without a working definition of perception, these ideas may get lost. The word perception seems to be used in various ways. Anderson (1983) notes that perception, at least in the realm of educative curricula, is usually characterized with respect to its dependence on visual stimuli. Woo (1994) describes one approach to understanding perception, however, as what we capture “via any of the senses” (p. 199) about an object, or document, to gather information. This “via any sense” definition is best suited for media that involve attributes, such as “physical, temporal, spatial and symbolic” attributes (Goodrum, 1997, p. 2). These include, for example, hue and proximity of objects in the image, motion of the camera, and the number of times and how often characters in the MID verbalize. In an action-oriented notion of perception, the perceiver is assumed to be continuously “sampling the ambient light for information of current value” (Feldman, 1987, p. 531). This is similar to information monitoring, where monitoring occurs as one is constantly watching or scanning surroundings in anticipation of information that could stimulate thought (O’Connor, 1996). Perception may involve three levels of analysis, or levels of explanation (Marr, 1982) as needed to program computers to perform visual tasks. Marr calls these levels computational theory, algorithms, and hardware. Regarding human perception, Roth and Frisbey (1986) describe these levels of explanation as 1) what
functions must perception achieve? 2) what are the operating principles which achieve these functions? and 3) what are the mechanisms underlying these operating principles. If one inserts the moving image documents and subjects of this study, we might better understand the role the children play in representation of documents intended specifically for them. That is, perception must achieve transforming the input of moving image documents into the outputs of verbal descriptions, non-verbal expressions, and judgement values of what was seen (Level 1). By achieving this much, the children will have already formed some representation (Level 2) of the document viewed with their own vision (Level 3). The age of the viewers is significant to document representation not only because developmental and cognitive abilities could limit content comprehension, but also because of the different degrees of difficulty form attributes bring to younger viewer perception (Collins, 1983). The operations of the functions of the act of perception (viewer representation) can be directly affected by complexity of the data stream.

Arnheim asserts that “perception involves problem solving” (Arnheim, 1967, p. 37). Perceiving attributes and forming opinions of MIDs is likely a result of having become, through exposure, a critical viewer—one who “evaluates the programs while watching” (Anderson, 1983, p. 313). The notion of critical viewing is an extension of the notion of critical thinking, which implies comprehension of the documents and extraction of meaning. The activity of this problem-solving approach to perception seems to dwell on program content and gives little or no regard for the form of the medium itself. This is a diversion from McLuhan’s (1964) assertion that the real effects of television are a result of the form of the medium. I assume children would be unaware of the effects of their
own insight, or passive perception, of nonverbal dependence, set constraint, or verbal time—that is, television form attributes—in the program they are watching.

An Integrated Concepts Model for Representations by Children

Watt’s form complexity in television programming, O’Connor and O’Connor’s representation palette, O’Connor’s signal bundle model, Marr’s levels of explanation for perception, Roth and Frisbey’s levels of analysis, and Maron’s aboutness, combined with the activity of seeing through the eyes of a child forms an integrated concepts model for representations by children. Figure 2.3. illustrates how this integrated model works.

Essentially, the child viewer perceives, through the acts of seeing and hearing, the physical complexity of the physical data stream of the moving image document. [That is not to say that the child does not also perceive content attributes of the MID, for she does; this model is mainly interested in the child’s perception of the form attributes.] The signal bundle is processed as data input by the child who forms some judgment about the signal in terms of perceived complexity of form aboutness in a temporal, audio-visual data stream. What has been perceived is a representation of the MID by the child viewer whose representation ideas are significant to the ways the MID could be assigned in an information retrieval system because the child’s developmental and cognitive abilities probably differ significantly from more mature viewers. Responses, or verbalizations, to the evolving representation are elicited from the child so that one more color can be added to the representation palette for this particular document, creating an access mechanism for age appropriate information seekers.
The inconvenient and seemingly impossible task of having every possible user of each MID view and provide verbalizations of their representations to each is foreboding. If child verbalizations of perceived form complexity could be calibrated to a measure constructed by a set of equations, representing each MID would not require eliciting verbalizations from every possible child viewer of every possible document. If the
responses of viewers were quantifiable and if a set of equations applied to the MID could demonstrate relationships between documents similar to the elicited verbalizations of children, then viewer perception of form aboutness could be represented by a single number in the information retrieval system. A vexing problem with information retrieval systems is the inability to perfectly combine all the various properties of every document with all the various properties of all users. The “probability of relevance” (Robertson, Maron, & Cooper, 1982), given these dubious odds, suggests that the relationship between MIDs and children’s perceptions of form complexity will not likely work for each and every child, but probably will for the general class of information seekers this age. Figure 2.4 illustrates the synchronizing of the Integrated Concepts Model for Representations by Children and a set of equations for representing viewers’ perceptions of form attributes in an MID.
Problem and Hypothesis

Can a correlation be established between calculated values of form complexity and child-viewer perception of form attributes in moving image documents designed specifically for child audiences? If the answer to this question is yes, then can calculable entropy measures (CEM) stand for children’s perceived entropy measures (PEM) in a surrogate of the MID to enrich representation for a particular user group? I propose that
mechanically derived CEM will be sufficiently similar to PEM made by children so that they can be used as useful and predictive elements of representations of children’s videos. CEM will predict level of viewer engagement with a document. Higher CEM will have a positive correlation with higher interest. Specifically, for seven to ten year old viewers, CEM and PEM will hold the same relationship to viewed documents.

Additional Thoughts

Document representation plays an important role in the field of information science. Researchers continue to develop new and richer means for describing documents of various formats in ways that are useful and meaningful to particular users while predicting document aboutness. Documents for children are no different. Libraries and other collections use the same guidelines for representing documents for adult and child patrons, when children are very different searchers with very distinct developmental abilities and needs that differ from adults. Wilson (1968) asserts that an index (or other types of access mechanisms) could be user-centered only if the indexer could view the document from the same perception as the user, indeed with the user’s own intellect and experiences. This is probably idealistic, but the notion of employing children’s own experiences, through their volunteered perceptions of moving image documents most certainly can enrich document representation for children’s media.
CHAPTER 3

MATERIALS AND METHODS

This research is exploratory with the intent of being a proof of concept. The essential premise of this research is that mechanically calculated entropy measures will be sufficiently similar to perceived entropy measures made by children that they can be used as useful and predictive elements in representations of children’s videos. The general hypothesis, as stated in the previous chapter is: Calculated Entropy Measures (CEM) will predict the level of viewer engagement with document, that is for seven to ten year old viewers, Calculated Entropy Measures (CEM) and Perceived Entropy Measures (PEM) will hold the same relationship to viewed documents because higher CEM will have a positive correlation with higher interest.

Four elements are required to support such a hypothesis: a method of mechanical calculation of entropy; one or more pairs of documents, each pair comprised of works on similar topics but with different entropies (resulting from different production styles); a group of viewers aged seven to ten years old; and an instrument for measuring perceived entropy of document viewers.

The effectiveness of entropy measures for television programming in general has been established by Watt (1979) and others (Watt & Krull, 1974; Watt & Welch, 1983), as elaborated in the previous chapter. These studies have shown that the tool is powerful and that it has worked in the past when applied to television programs. There has been no
application of this tool to documents for children, especially for use in representations of those documents. The calculation of entropy measures is straightforward. The application of Watt’s formulae to the test documents is detailed in the subsequent chapter on data analysis. Use of these formulae is based on the premise that information is a quantity and that the measure of the quantity of information is the measure of the unforeseeable, or unexpected (Moles, 1966, p. 19).

Selecting documents for the test collection required criteria for similarity of topic and difference of production attributes sufficient to result in significantly different calculated entropy measures. An earlier examination of commercial representations of children’s videos provided a mechanism for selection.

Establishing an instrument to measure the perceived entropy judgments of children was the primary challenge for determining the efficacy of entropy measures as a means of representation of children’s videos. Adaptation of a scaling instrument together with ethnographic methods provided an effective approach.

Materials: Selected Moving Image Documents

In a previous study, in which I examined established representation tools for educational television (namely TV Guide, TV Chronicle, and tvguide.com) for strength and sufficiency of representation, I determined that, of these tools, tvguide.com enlisted the most functional and thorough descriptions available to general users (see Table 3.1 and Figure 3.1).
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Table 3.1: Distributions of Three Descriptors for Educational Television Programming on a Friday at 8:00PM

Figure 3.1: Comparison of Total Extractable Keywords

With the help of these findings and tvguide.com, four MIDs were selected for this study. These descriptions demonstrate that pairs of MIDs that provide similar information were selected. Each pair of MIDs contains segments from one program intended for adult audiences and from one program intended for children.
The tvguide.com description for MID1a is as follows:

Wild Discovery
“Creatures of the Magic Water”
60 min.

A look at the unusual wildlife that thrives along South America's flooded lowland rivers during the Amazon's rainy season. Included: the giant otter; the manatee; the jaguarundi.

Rating: TV-G
Category: Documentary
The tvguide.com description for MID1b is as follows:

Zoboomafoo
“Hail to Tails”
30 min.

A visit by a kinkajou prompts discussion of prehensile (grabbing) tails. Then Jackie visits some newborn kittens and learns not to grab their tails.

Cast: Samantha Tolkacz
Rating: TV-Y
Category: Children, Educational
Release Year: 2000

One can see in both the tvguide.com descriptions and the selected key frames (see Figures 3.2 and 3.3 and Appendixes B and C) for MID1a and MID1b that both MIDs communicate similar information. These particular programs are both about unusual animals (manatee, jaguarundi, kinkajou). MID1a is categorized as a documentary (assumed for an adult audience) and MID1b is categorized as an educational children’s program.

Moving Image Documents 2a and 2b

Figure 3.4: Selected Key Frames from MID2a
The tvguide.com description for MID2a is as follows:

Best of The Joy of Painting
30 min.
Category: Arts & Literature

![Selected Key Frames from MID2a]

Figure 3.5: Selected Key Frames from MID2b

The tvguide.com description for MID2b is as follows:

Out of the Box
30 min.
Two caregivers teach youngsters how to explore their everyday surroundings.
Rating: TV-Y
Category: Children, Educational

This second set of MIDs contains information about arts and crafts. The selected keyframes for each (Figures 3.4 and 3.5 and Appendixes D and E) show this common theme. The tvguide.com descriptions for these programs are less representative of the actual document than the descriptions for the MID1 set. Both programs are given generic descriptions that fit all episodes of each series. MID1a is categorized as arts and literature (assumed for an adult audience) and MID1b is categorized as an educational children’s program.
Subjects

With the approval from the University of North Texas Institutional Review Board for Human Subjects (see Appendix G) and permission from parents, 13 subjects were chosen from a convenient sample to form a uniform group of viewers. All subjects were girls aged 7 to 10 years. Because all the subjects are friends of my daughter, I decided to run the experiment in my home to give the girls a familiar environment where they would possibly be more comfortable than in a classroom or digital lab setting.

In groups of three and four, 13 girls were shown two video clips communicating similar information (see Table 3.2).

<table>
<thead>
<tr>
<th>Subject</th>
<th>MIDs Shown</th>
<th>Age of Subjects</th>
</tr>
</thead>
<tbody>
<tr>
<td>A, B, M*</td>
<td>MID1a &amp; MID1b</td>
<td>8, 9, 8</td>
</tr>
<tr>
<td>C, D, E, F</td>
<td>MID1a &amp; MID1b</td>
<td>10, 7, 8, 10</td>
</tr>
<tr>
<td>G, H, I</td>
<td>MID2a &amp; MID2b</td>
<td>8, 8, 8</td>
</tr>
<tr>
<td>J, K, L</td>
<td>MID2a &amp; MID2b</td>
<td>8, 8, 9</td>
</tr>
</tbody>
</table>

Table 3.2: Groups of subjects, MIDs shown, and ages of subjects

While viewing, subjects were videotaped. The video camera was located off to the side but between the television and the children (see Figure 3.6) to capture clear reactions while not being the main focus of attention. I sat and observed at a table behind the camera and the subjects were instructed not to speak to me for the duration of the MIDs.

After viewing, subjects were interviewed individually and asked to talk about what they saw. These stories were also videotaped. Videotaping was done so that later analysis could be accomplished on the entropy in the reactions of subjects. Finally, individual children were asked to make comparative judgements of what they had seen by plotting stickers on line graphs as a way of turning their perceptions into quantifiable data. [Note: Subject M was excluded from the study for reasons expressed in the following chapter.]
Figure 3.6: Subjects G, H, & I and Subjects C, D, E, & F (with faces blurred for confidentiality.)

An Instrument for Measuring PEM: Comparative Judgements

Comparative judgments quantify responses elicited from subjects. Comparative judgements provide “a rationale for ordering objects on a psychological continuum. Psychological objects are stimuli for which some reaction takes place within the sensory system of the individual” (Dunn-Rankin, Knezek, Wallace, & Zhang, p.96). For eliciting judgments from children, dots made on line graphs displaying polar reactions to certain questions, as in Figure 3.7, have proven robust (Dunn-Rankin, personal communication, October 2000). Actual comparative judgment questionnaires are presented in Appendix A. The questions asked for each line graph were expected to elicit feelings about the changes in the program information viewers may have felt after watching an MID. These emotive descriptions—interest, exciting, like, funny, boring, surprising—were adjectival representations of entropy distilled from numerous authors and naïve respondents, following the examples of Weaver (1949) who used “confusing” (p. 117); Augst and O’Connor (1999) who used “dull” (p. 357) and “dynamic” (p. 355); Watt
(1979) who used “exciting” (p.56), “interest” and “boring” (p. 68); and Campbell (1983) who used “dull” and “exciting” (p.67).

Children were asked to place the sticker anywhere on the line graphs to express their feelings about each MID. The position of a sticker on the graph determined its numeric value. For example, Figure 3.8 shows how one child’s assessment of an MID translates to the numeric value 0.625, which can then be compared to the corresponding CEM.
<table>
<thead>
<tr>
<th>MID2a</th>
<th>How funny was the 1st video?</th>
<th>MID2b</th>
<th>How funny was the 2nd video?</th>
</tr>
</thead>
<tbody>
<tr>
<td>not funny</td>
<td>very funny</td>
<td>not funny</td>
<td>very funny</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>MID1a</th>
<th>How exciting was the 1st video?</th>
<th>MID1b</th>
<th>How exciting was the 2nd video?</th>
</tr>
</thead>
<tbody>
<tr>
<td>not exciting</td>
<td>very exciting</td>
<td>not exciting</td>
<td>very exciting</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>MID2a</th>
<th>Would you want to see the 1st video again?</th>
<th>MID2b</th>
<th>Would you want to see the 2nd video again?</th>
</tr>
</thead>
<tbody>
<tr>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
</tr>
</tbody>
</table>

Figure 3.7: Sample polar reaction line graphs used for children to rank opinions of MIDs based on comparative judgements
The girls’ individual stories were recorded for later analysis of precise material to evaluate for perceived entropy values. I anticipated that these interviews would support the comparative judgements subjects would make immediately following viewing. The videotaping caught subjects’ descriptive words, including those involved in group interactions, during the viewing, and retrospective descriptions. These stories plus subjects’ responses to direct questioning of the videos comprise the data for determining perceived entropy values.

This study is not about child psychology but about children’s perceptions of moving image documents for the purpose of creating representations of these documents with greater utility for the target age group. As described in Chapter 2, if children’s perceptions of MIDs can be correlated to calculated entropy measures with an established equation, then subsequent children’s likely perceptions could be represented with the calculable entropy measures.
Statistical Analysis

A normalized mean score for each comparative judgment was calculated from the polar reaction graphs from the children. Raw scores on the line graphs were made into percentages to standardize the scores (shown in Figure 3.8). The mean score for each comparative judgment within a pair of videos was compared by using a Student’s $t$-test (paired, two-tail). The $t$-test compares two means. A paired test indicates that there is a constant relationship between the two means, in this case, between a child’s perceptions of one MID (say, MID1a) and the corresponding MID (MID1b). A two-tailed factor asserts that there is no a priori prediction about the relationship of the data and that the test is being performed to determine any significant difference in the children’s quantified perceptions. The overall mean score for each pair of videos was also tested in the same manner. In order to have reliable $t$-test results, the data have to meet two assumptions: data have to be normally distributed, and data have to have equal variance. If either of these assumptions was not met, then the Signed Rank test was used. Normality is determined by software. In non-normal data, the Signed Rank test is performed on the ranked information and not on the data itself. The level of significance was set at $P < 0.05$. All tests were performed using the software package SigmaStat® (SPSS Inc.).
CHAPTER 4

DATA ANALYSIS

Calculating Wattian Entropy

By understanding a single fundamental premise we can take Shannon’s original entropy equation (shown in Figure 4.1) and apply it to many forms of communication, in this case to moving image documents. It is essential to see that “information is a measurable quantity which characterizes the process of communication” (Moles, p. 196).

\[ H = - \sum_{i=1}^{k} p_i \cdot \log_2(p_i) \]

Figure 4.1: Shannon’s original Entropy equation

Based on modifications to Shannon’s statistical model of data transmission, the model established by Watt and Krull (1974) and elaborated by Watt (1978) to calculate useful entropy measures for each moving image document by using seven entropy formulae—one for each of seven types of “form attribute” common to moving image documents. The first six were developed after Watt examined 168 television programs from 58 series. The following chart (Figure 4.2) presents the formulae and verbal definitions.
| **Set Time Entropy** (HST, where H is Entropy) | the degree of randomness of the time of visual duration of discrete physical locations in a program | \[ \sum_{i=1}^{k} \frac{k_{set}}{t_{show}} \log_2 \frac{k_{set}}{t_{show}} \] where \( t_{set} \) = total time the \( i \)th set appears \( t_{show} \) = total time of the show \( k \) = number of sets |
| **Set Incidence Entropy** (HSI) | the degree of randomness of the appearance of discrete physical locations in a program | \[ \sum_{i=1}^{k} \frac{n_{set}}{n_{set show}} \log_2 \frac{n_{set}}{n_{set show}} \] where \( n_{set} \) = number of times the \( i \)th set appears \( n_{set show} \) = number of times all sets appear in the show \( k \) = number of sets |
| **Verbal Time Entropy** (HVT) | the degree of randomness of the time of audible behavior on the part of characters in a program | \[ \sum_{i=1}^{k} \frac{k_{char}}{t_{verbal}} \log_2 \frac{k_{char}}{t_{verbal}} \] where \( k_{char} \) = total time the \( i \)th character produces sound \( t_{verbal} \) = total verbal time \( k \) = number of characters |
| **Verbal Incidence Entropy** (HVI) | the degree of randomness of the performance of audible behavior on the part of characters in a program | \[ \sum_{i=1}^{k} \frac{k_{char}}{n_{char show}} \log_2 \frac{k_{char}}{n_{char show}} \] where \( n_{char} \) = number of times \( i \)th character verbalizes \( n_{char show} \) = total verbalizations in show \( k \) = number of characters |
| **Set Constraint Entropy** (HSC) | the degree of randomness of the constraints of the discrete physical locations in a program | \[ t_{inside} \log_2 \frac{t_{inside}}{t_{show}} \] where \( t_{inside} \) = total time spent with indoor locations \( t_{show} \) = total time of the show |
| **Nonverbal Dependence Entropy** (HNV) | the degree of randomness of the use of only visuals to carry the narrative | \[ t_{show} - t_{verbal} \log_2 \frac{t_{show} - t_{verbal}}{t_{show}} \] where \( t_{verbal} \) = total verbal time for all characters \( t_{show} \) = total time of the show |

Figure 4.2: Key to Wattian Entropy Measure adapted from Watt (1978) pages 61-63.
Even Watt acknowledges that these are not the only components of MIDs that can be measured. For this study, a seventh formula was added to the original series, that measures the number of times characters walk in and out of the viewing space. This measure is termed Character Appearance Entropy (HCA) and is described in the following chart (Figure 4.3).

| Character Appearance Entropy (HCA) | the degree of randomness of the appearance of characters in the program | $-\frac{t_{\text{appearance}}}{t_{\text{show}}} \log_2 \frac{t_{\text{appearance}}}{t_{\text{show}}}$ | where $t_{\text{appearance}}$=total number of times characters enter and exit the set $t_{\text{show}}$=total time of the show |
|-----------------------------------|---------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|

Figure 4.3: Additional Entropy Element

The calculations for the four moving image documents selected for this research, as described in Chapter 2, are shown in Table 4.1. The measures range from zero to 0.527. [The original formula involves the summation of applicable elements (Set Incidence, Nonverbal Dependence, and so on). This study calculates the mean of the elements for each application of the equation in order to limit the scale to values between zero and one for the purpose of calibrating CEM to PEM on the same scale. Alternative methods have been used to calculate rate of change in communications. Augst and O’Connor (1999), for example, calculate rates of change in two videos without explicitly using Shannon’s original formula. The method used in this study adapts the original formula to suit these operations. Appendix H presents a comparison between CEM scores implementing summation and CEM scores implementing mean; similar relationships result. The Wattian formulae are designed to calculate a numeric entropy value that lies between zero and one. It was first intriguing to discover that in MID2a, which consists of
a man painting a picture, Set Constraint Entropy (HSC) equals zero. Before the
calibration, I had naively anticipated that this measure would be high since the character
spends the entire time of the clip indoors. (Recall that HSC is calculated by comparing
the total time spent indoors to the total time of the show.) Of course I soon realized,
however, since there is no variation, that is, since the set is constrained to a single indoor
setting, entropy is very low; in fact there is zero rate of change for the message with
respect to this particular measure. Likewise, HSC for MID1a equals zero since the entire
message is constrained to outdoor settings and has no variation or no change in the rate of
information for the HSC measure.

Immediately obvious in the entropy calculations for MID Test Set (Table 4.1) is
the large number of zero values, especially for MID2a. On the face of it, this might seem
contrary to expectation. For example, the Set Constraint measure for MID2a reflects a
program in which the one character spends the entire length of the clip in the same indoor
set. Recall that HSC compares the total time indoors to the total time of the clip. MID2a
would have presented a simple ratio of 1, since the time indoors equals the total length of
the clip. However, multiplication by the log value (in this case, zero) yields a value
reflective of the rate of change. Likewise, the HSC for MID1a equals zero since the entire
message is constrained to outdoor settings and displays no variation on this form
attribute.
Table 4.1: Entropy Calculations for MID Test Set

<table>
<thead>
<tr>
<th></th>
<th>MID1a</th>
<th>MID1b</th>
<th>MID2a</th>
<th>MID2b</th>
</tr>
</thead>
<tbody>
<tr>
<td>HST</td>
<td>0.333</td>
<td>0.285</td>
<td>0.000</td>
<td>0.136</td>
</tr>
<tr>
<td>HSI</td>
<td>0.519</td>
<td>0.491</td>
<td>0.000</td>
<td>0.500</td>
</tr>
<tr>
<td>HVT</td>
<td>0.000</td>
<td>0.484</td>
<td>0.000</td>
<td>0.400</td>
</tr>
<tr>
<td>HVI</td>
<td>0.000</td>
<td>0.461</td>
<td>0.000</td>
<td>0.407</td>
</tr>
<tr>
<td>HNC</td>
<td>0.000</td>
<td>0.214</td>
<td>0.000</td>
<td>0.092</td>
</tr>
<tr>
<td>HNN</td>
<td>0.498</td>
<td>0.411</td>
<td>0.134</td>
<td>0.527</td>
</tr>
<tr>
<td>HCA</td>
<td>0.168</td>
<td>0.393</td>
<td>0.000</td>
<td>0.506</td>
</tr>
<tr>
<td>(xH)</td>
<td>0.217</td>
<td>0.391</td>
<td>0.019</td>
<td>0.367</td>
</tr>
</tbody>
</table>

Similar results are found with Verbal Time Entropy (HVT) and Verbal Incidence Entropy (HVI) (where HVT is measured by the average of the number of times each character produces sound over the total verbalization time of the clip and HVI is measured by the average of the number of times each character verbalizes over the total number of verbalizations in the clip). For example, both MID1a and MID2a have single character verbalizations. The narrator in MID1a speaks only seldom compared to the total time of the show. The painter in MID2a speaks for nearly the entire ten-minute clip. Because of his constant verbalization, entropy measures will be low because there is no variation in the rate of information for verbal incidence and verbal time. In addition, those MIDs for which entropy measures are calculably high do not exceed half the way point on the scale, showing that MIDs with high or low occurrences of the specific elements being measured in the formula (low occurrence of verbalization is coupled with high non-verbalization) produce entropy measures lower on the scale; and that medium occurrences of specific elements (such as shared verbalization time between characters, or equal amounts of verbal and nonverbal time) measure higher on the same scale. Using the Virage® Video Logger, keyframes were extracted from the MIDs at the sensitivity
level 20 (see Appendixes B, C, D, E). The numbers of keyframes extracted show the same relationships between sets of MIDs. [Note: The precise number of keyframes extracted may not correlate exactly with a viewer’s concept of significant rate of change in the data stream. Keyframes extracted by Virage® are grabbed at points of detectable change in the data stream that may not necessarily coincide with a viewer’s concept of significant changes. No image (a black frame) and two frames containing the same image with different clarity—as in the first three keyframes of the Mr. Roger’s Neighborhood (see Figure 1.5) set at sensitivity level 20—are not discrete or valuable in the representation of the full document.]

Watt and Krull (1974, p.58) speak to the idea of variety setting up an expectation of unfamiliarity. One might speculate about the HSC of MID1a and MID2a that there might have been some expectation on the part of viewers for a while that there would be some change until sufficient time had passed to establish the likelihood there would be no change. As the frequency of an attribute increases, the unfamiliarity (likelihood of surprise) goes up, but only to a point. Since entropy reflects probabilities of appearance, very high frequency decreases surprise, and lowers entropy.

Based on these calculated entropy figures, comparisons of the relationships between the MIDs in each set are shown in Figure 4.6. MID1b has an entropy measure of nearly twice that of MID1a. [Table 4.2 describes MIDs as first shown in Chapter 3.]
MID1b, though having a higher calculated entropy measurement, is only approximately 0.17 units higher on a scale from 0 to 1 than the calculated entropy value for MID1a. In contrast, the relationship between the calculated entropy measurements for MID2a and MID2b is visibly significantly different from the MID1 set. These materials intended for child audiences both have calculated entropy measures that are higher than the similar subject MIDs intended for adult viewers. The MID2 set of values could be interpreted as being more dramatically separated, possibly indicating variety in anticipated viewer responses because the rates of information in these messages are so different, if, in fact, the rates of information are intentional.
| MID1a | Wild Discovery: “Creatures of the Magic Water” |
| MID1b | Zoboomafoo: “Heads to Tails” |
| MID2a | Best of The Joy of Painting |
| MID2b | Out of the Box |

Table 4.2: Descriptions of Moving Image Documents

These formulae make sense only with an a priori assumption that the original formula for determining entropy, based on the research of Shannon and Weaver (1949), has validity. The widespread use of the formula as implemented by many researchers across various disciplines (Watt (1979), Watt & Welch (1983), Moles (1966), Pierce (1961) to name a few) would support this assumption. Even the work of O’Connor and Augst (2000), while it does not expressly use Watt’s formulations, demonstrates the same relationships between rates of change in the data stream and audience perceptions.

Within each of the entropy formulae, it was necessary to define specific units of measurement. What unit of time should be used? What is the basic unit for set determination? What distinguishes a character versus a set of characters as a single unit? What constitutes a verbalization?
Some of these questions require only simple answers. Seconds were used as the most practical basic unit of time. That is, one second increments have fine enough resolution to capture all significant discontinuities without yielding undue amounts of “noisy” data (see Figure 4.5). Several of the entropies required timing verbalization time.

Figure 4.5: Ulead® Video Editor showing MID1a in one second intervals

With the video editing software, Ulead® Video Editor (see http://www.ulead.com/msp/VE_U1.htm), used for the calculations, any visual element could be measured precisely by cutting and pasting the video into smaller segments to show, for example, the total time of one specific set. The smallest unit of time could have been the single frame, 1/30th second. For non-visual components, this same process could not be used. To figure the amount of time each individual character speaks, an external timer was required, which used seconds as the smallest unit of time.

In order to calculate Set Incidence Entropy (HSI), the set unit needed to be established for each MID. For MID2a, this was quite straightforward: the painter never
moved from his easel. The sets in the other MIDs were not so obvious. MID1a was filmed entirely outdoors in three general locations: land, water, and sky. These are the sets, then, that were used to determine HSI for MID1a, though these same divisions may not have been what sophisticated software would have selected. [Recall the discussion in Chapter 1 about the sensitivity levels in the Virage Video Logger (see Figures 1.5 to 1.8). What I called a “background scene change” was different from what the software noted as a significant change in the physical data stream.] A camera move from a point on the surface of the water in shade to a point reflecting light, for example, would have been considered two separate elements by virtue of variations in the data stream, but was held as a single conceptual element.

Single characters usually formed obvious divisions from one another. In MID1a, however, hundreds of turtles hatch from their eggs and scurry into the water. The scurrying turtles were counted as a single character event. MID1b featured animals, puppets, and cartoons as main and secondary characters, these characters were given the same character status as their human co-hosts.

Similarly, verbalizations were separated into individual verbalization events. A single character’s speaking up until another character speaks was considered a verbalization event. MID1a and MID2a had single verbalization events causing the rate of information in these particular messages to be low. What can be considered a single verbalization event? One man speaks, in MID1a, and the other laughs. Is the laugh a verbalization event? If instead of a laugh, it’s a knowing “Hmm!” or a grunt, is it a verbalization event? Each grunt, or hmm, or laugh was judged within the circumstances of the video to determine its verbalization eventfulness. Consider Oscar the Grouch
moaning: this is a significant verbalization for this particular character. In contrast, Dan Rather’s “ahem” during a news broadcast is probably not significant.

Certainly there are other ways these elements could be measured, since the divisions in all the entropy formulae for unit of time, verbalization events, changes in set, and character events are all formed on the basis of detectable changes in the data stream, together with an understanding of the coding system that ordinarily constrains the clustering of such changes. Subsequent research might well include entropy measures based solely on software detected discontinuities, though even then the issue of what constitutes a significant discontinuity remains problematic.

Comparative Judgments of Moving Image Documents

Each subject was asked individually to make a comparative judgment of one set of moving image documents by placing a green, quarter-inch sticker on a line to visually express their opinions of the MIDs. The subjects were asked six questions. Each line divided precisely into 40 quarter-inch units so that numeric representations of each subject’s comparative judgments could be calculated. Two comparative judgment samples from one subject are shown in Figure 4.6. (Spacing between actual lines is one-half inch.)
Would you want to see the 1st video again?

Would you want to see the 2nd video again?

How exciting was the 1st video?

How exciting was the 2nd video?

Figure 4.6: Comparative Judgments Samples for MID2a and MID2b

The other comparative judgments the subjects were asked to quantify are

How much do you like the 1st video?
How much do you like the 2nd video?

How funny was the 1st video?
How funny was the 2nd video?

How boring was the 1st video?
How boring was the 2nd video?

How surprising was the 1st video?
How surprising was the 2nd video?
Each comparative judgment was assigned a numerical representation between zero and one. The results are shown in Table 4.3, and are displayed both as averages for each child and group averages for each question. The mean normalized score of MID1b was significantly higher than MID1a (P=0.003). Similarly, the mean normalized score of MID2b was significantly higher than MID2a (P=0.003). Specifically, the children thought MID2b was both significantly more exciting (P=0.026) and significantly more funny (P=0.041) than MID2a.
<table>
<thead>
<tr>
<th></th>
<th>again</th>
<th>exciting</th>
<th>like</th>
<th>funny</th>
<th>not boring</th>
<th>surprising</th>
</tr>
</thead>
<tbody>
<tr>
<td>MID1A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>a</td>
<td>0.600</td>
<td>0.600</td>
<td>0.900</td>
<td>0.450</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>b</td>
<td>0.900</td>
<td>0.450</td>
<td>0.750</td>
<td>0.900</td>
<td>1.000</td>
<td>0.650</td>
</tr>
<tr>
<td>c</td>
<td>0.200</td>
<td>0.300</td>
<td>0.600</td>
<td>0.100</td>
<td>0.100</td>
<td>0.250</td>
</tr>
<tr>
<td>d</td>
<td>0.600</td>
<td>0.350</td>
<td>0.45</td>
<td>0.050</td>
<td>0.550</td>
<td>0.500</td>
</tr>
<tr>
<td>e</td>
<td>0.500</td>
<td>1.000</td>
<td>0.95</td>
<td>0.900</td>
<td>0.700</td>
<td>0.000</td>
</tr>
<tr>
<td>f</td>
<td>0.350</td>
<td>0.550</td>
<td>0.5</td>
<td>0.050</td>
<td>0.600</td>
<td>0.650</td>
</tr>
<tr>
<td></td>
<td>0.525</td>
<td>0.5417</td>
<td>0.692</td>
<td>0.408</td>
<td>0.658</td>
<td>0.508</td>
</tr>
<tr>
<td>MID1B</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>a</td>
<td>0.850</td>
<td>0.650</td>
<td>0.950</td>
<td>1.000</td>
<td>1.000</td>
<td>0.950</td>
</tr>
<tr>
<td>b</td>
<td>1.000</td>
<td>0.950</td>
<td>1.000</td>
<td>0.500</td>
<td>1.000</td>
<td>0.850</td>
</tr>
<tr>
<td>c</td>
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<td>0.300</td>
</tr>
<tr>
<td>d</td>
<td>0.150</td>
<td>0.150</td>
<td>0.250</td>
<td>0.150</td>
<td>0.200</td>
<td>0.300</td>
</tr>
<tr>
<td>e</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.950</td>
<td>0.100</td>
</tr>
<tr>
<td>f</td>
<td>0.650</td>
<td>0.700</td>
<td>0.750</td>
<td>0.800</td>
<td>0.650</td>
<td>0.500</td>
</tr>
<tr>
<td></td>
<td>0.708</td>
<td>0.658</td>
<td>0.783</td>
<td>0.700</td>
<td>0.775</td>
<td>0.500</td>
</tr>
<tr>
<td>MID2A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>g</td>
<td>0.975</td>
<td>0.025</td>
<td>0.975</td>
<td>0.025</td>
<td>0.975</td>
<td>0.025</td>
</tr>
<tr>
<td>h</td>
<td>0.000</td>
<td>0.000</td>
<td>0.400</td>
<td>0.000</td>
<td>0.100</td>
<td>0.200</td>
</tr>
<tr>
<td>i</td>
<td>0.700</td>
<td>0.950</td>
<td>1.000</td>
<td>0.150</td>
<td>1.000</td>
<td>0.500</td>
</tr>
<tr>
<td>j</td>
<td>0.600</td>
<td>0.700</td>
<td>0.750</td>
<td>0.000</td>
<td>0.750</td>
<td>0.650</td>
</tr>
<tr>
<td>k</td>
<td>0.000</td>
<td>0.550</td>
<td>0.550</td>
<td>0.000</td>
<td>0.550</td>
<td>0.500</td>
</tr>
<tr>
<td>l</td>
<td>0.600</td>
<td>0.150</td>
<td>0.550</td>
<td>0.000</td>
<td>0.400</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>0.479</td>
<td>0.396</td>
<td>0.704</td>
<td>0.029</td>
<td>0.629</td>
<td>0.321</td>
</tr>
<tr>
<td>MID2B</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>g</td>
<td>0.875</td>
<td>0.875</td>
<td>0.725</td>
<td>0.475</td>
<td>0.725</td>
<td>0.125</td>
</tr>
<tr>
<td>h</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.450</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>i</td>
<td>0.925</td>
<td>0.950</td>
<td>1.000</td>
<td>0.100</td>
<td>1.000</td>
<td>0.500</td>
</tr>
<tr>
<td>j</td>
<td>0.600</td>
<td>0.850</td>
<td>0.800</td>
<td>0.200</td>
<td>0.750</td>
<td>0.650</td>
</tr>
<tr>
<td>k</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>l</td>
<td>1.000</td>
<td>0.650</td>
<td>1.000</td>
<td>0.300</td>
<td>1.000</td>
<td>0.350</td>
</tr>
<tr>
<td></td>
<td>0.900</td>
<td>0.888</td>
<td>0.921</td>
<td>0.421</td>
<td>0.913</td>
<td>0.604</td>
</tr>
</tbody>
</table>

Table 4.3: Numerical Representations of Comparative Judgments for MIDs
The mean for each MID, that is, the average of the total perceived entropy scores, can be translated into the following chart, Figure 4.7. One can see that the relationships between the perceived entropy values show similarities to the relationships between the calculated entropy values of Figure 4.4, in that MID1a and MID2a demonstrate lower scores than those of MID1b and MID2b respectively. The actual numerical values are not the same, however the relationships between the sets of MIDs suggest that a calculated entropy value could render a numeric representation for these and other moving image documents for child audiences that reflect the opinions of the child viewers. Figure 4.8 shows similar relationships between the sets of MIDs. Thus, the data support the hypothesis that there would be a significant positive correlation between mechanically calculated entropy scores for a set of MIDs and the reactions of children viewing the MIDs.

![Comparison of Perceived Entropy Values](image)

*Figure 4.7: Comparisons of Perceived Entropy Values*
Watt (1978) addresses the idea that the transmission of data does not completely outweigh the topic of the moving image document. The proportion (shown as a percentage) of the PEM measures in both MID sets to each other are closer than the proportion of the CEM measures (comparisons shown in Figure 4.8). The proportion of PEM of MID1a to MID1b is 80.8% while CEM of MID1a to MID1b is 55.5%. Similarly, PEM of MID2a to MID2b is 55.1% whereas CEM of MID2a to MID2b is 5.2%. These relationships possibly indicate that the topic has some bearing on perceived entropy, since form complexity does not negate viewer perceptions of content. This is confirmed in the interviews with the subjects (see Figure 4.9), during which subjects verbalized perceived elements of content attributes.

![Calculated Versus Perceived Entropy](image)

Figure 4.8: Calculated and Perceived Entropy Compared

One additional question was given to each subject: How much do you like birthday parties? This question and the responses to it worked as a model for determining
if each child did, in fact, understand the comparative judgment process. As a result of this test, one child was eliminated from the study. In addition, her verbal responses to the MIDs and her comparative judgment representations did not match. For example, she claimed to enjoy MID1b and to be bored with MID1a, although she assigned equal values to the questions: How boring was the 1st video? and How boring was the 2nd video?; and How much do you like the 1st video? and How much do you like the 2nd video? Her reactions to the MIDs were opposite those of her peers. She often laughed inappropriately during the videos, and her peers told her “That’s not even funny.” Further, when I questioned her mother about normal behavior for this child, I learned that she has been diagnosed with a condition that required behavior altering medication at the time the sample was taken.

Table 4.4 displays comparisons made between the calculated entropy measure, the perceived entropy measure, and the number of keyframes extracted by Virage® Video Logger set at sensitivity level 20 (as seen in Appendixes B, C, D, & E). The measurements for MID1b and MID2b are consistently greater than the measurements for MID1a and MID2a, respectively. When these values are adjusted so that the lower number (CEM) equals 1, one can see a clearer relationship between the three sets of values. Further, a two-way analysis of variance (ANOVA) on the measurements show significant differences between the mean scores of each video (P<0.001), but that these differences do not depend on the method of measurement (PEM or CEM; P=0.790). In other words, CEM could stand for a surrogate of PEM. Table 4.5 shows that, in all three measurements, the MID1 set holds a closer relationship to each other than the MID2 set, that is the difference between measurements for MID1a and MID1b is smaller than the
difference between MID2a and MID2b. Though the numerical representations of the relationships vary—with particular attention to CEM of MID2a—the relationships themselves remain the same throughout the three methods of representation.

<table>
<thead>
<tr>
<th>MID</th>
<th>CEM</th>
<th>PEM</th>
<th># of keyframes extracted</th>
</tr>
</thead>
<tbody>
<tr>
<td>MID1a</td>
<td>0.217</td>
<td>0.556</td>
<td>110</td>
</tr>
<tr>
<td>MID1b</td>
<td>0.391</td>
<td>0.688</td>
<td>165</td>
</tr>
<tr>
<td>MID2a</td>
<td>0.019</td>
<td>0.426</td>
<td>99</td>
</tr>
<tr>
<td>MID2b</td>
<td>0.367</td>
<td>0.774</td>
<td>156</td>
</tr>
</tbody>
</table>

Table 4.4: Comparisons of CEM, PEM, and Number of Keyframes Extracted at Sensitivity Level 20 by Virage® Video Logger

<table>
<thead>
<tr>
<th>MID</th>
<th>Comparison</th>
<th>PEM</th>
<th># of keyframes extracted</th>
</tr>
</thead>
<tbody>
<tr>
<td>MID1a:MID1b</td>
<td>1:1.8</td>
<td>1:1.2</td>
<td>1:1.5</td>
</tr>
<tr>
<td>MID2a:MID2b</td>
<td>1:19.2</td>
<td>1:1.8</td>
<td>1:1.6</td>
</tr>
</tbody>
</table>

Table 4.5: Comparisons of CEM, PEM, and Number of Keyframes Extracted at Sensitivity Level 20 by Virage® Video Logger of MID Sets

Additional Approaches to Correlating Calculated and Perceived Entropy

Table 4.6 compares the mean to the mode and median values for the numerical representations of the perceived entropy values shown in Table 4.3. These data support the same high and low values as with the perceived entropy mean and the calculated entropy values, in addition to the similar relationships between MIDs in each set. MID1a and MID2a have lower means and medians than MID1b and MID2b and there is a lesser gap between the MID1 set of values than the MID2 set of values. These numbers, too,
support the hypothesis that a robust positive correlation holds between the calculable entropy formulae and the perceived entropy values of child viewers.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Mode</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>MID1a</td>
<td>0.556</td>
<td>0.600</td>
<td>0.575</td>
</tr>
<tr>
<td>MID1b</td>
<td>0.688</td>
<td>1.000</td>
<td>0.750</td>
</tr>
<tr>
<td>MID2a</td>
<td>0.4264</td>
<td>0.000</td>
<td>0.500</td>
</tr>
<tr>
<td>MID2b</td>
<td>0.774</td>
<td>1.000</td>
<td>0.900</td>
</tr>
</tbody>
</table>

Table 4.6: Mean, Mode, Median for Numerical Representations

The interviews videotaped with the children after they viewed the MIDs provided no additional insights, yet they support the general trend of the numeric comparative judgments of each child. Not all interview comments by the children were audible on the videotape. Their comments are shown in Figure 4.9. As was the case with both the calculated and perceived entropy values, the comments support a closer relationship (more similarities) between the MID1 set of videos than the MID2 set. When asked, “How did you feel about the first video?” (regarding MID2a), one child said “Boring,” while another child said “I like painting.” These responses reflected their comparative judgments, as the first child’s total score for MID2a was 0.117 and the second child’s was 0.717. When asked the same question of MID2b, one child indicated that she liked the video, but that it was a video for children younger than she. Her comparative judgment score for how much she liked MID2b was 0.725, showing that indeed she rated her enjoyment high, but not as high as her rating for MID2a, which scored 0.975 for the same judgment. Another child asserted “I like them both just the same;” her scores for MID1a and MID1b were 0.717 and 0.746 respectively. However, it is likely that interview comments reflect perceived notions of program content, and not form alone,
since the children’s responses were about program content, whereas responses elicited through comparative judgments likely reflect perceived notions of program form complexity.

One curious observation in the interviews shows the youngest child (almost eight years old) describing MID1b as a program for small children, supported with her comparative judgment score of 0.200. She rated MID1a higher, 0.417, though her scores are much lower than the scores of the other children who watched this video set. The oldest child in the group (just turned ten years old), on the other hand, described MID1b as one of her favorite programs on television, and gave it an overall rating of 0.625. She describes MID1a as just “okay” and scores it 0.258. Again, content and developmental level play a role—form entropy is not the sole determinant.

I had thought originally that entropy measures could be calculated on the viewing reactions of the subjects to see if there was any correlation between higher entropy videos and high entropy reactions. Such a relationship was observable. The first group of girls who viewed the MID2 set of videos, for example, jumped up and banged on the coffee table like a drum when they were invited to do so by the characters in MID2b. They also chatted throughout their viewing time about the content of the videos. Movement and conversation was observably much greater during viewing MID2b than MID2a. The second group of girls to view the MID2 set also chatted and asked each other questions about the videos with the same observable behaviors. While no frame by frame measurements were made, these relationships were supported by the Virage® Video Logger set at sensitivity levels 20 and 50, shown in Tables 4.7 and 4.8. [Table 4.7 displays the actual number of keyframes extracted from the video recording of each set of
viewers. Most keyframes extracted at both sensitivity levels 20 and 50 were a result of glitches in the data stream, not a result of significant movement of the subjects. Table 4.8 displays the number of the extracted keyframes that could represent significant movement of the subjects.] The results of the keyframe extractions at two sensitivity levels for all videotaped viewings are shown in Appendix F.

The groups of girls who watched the MID1 set of videos did not chat or move, except to scratch or twitch, during either video. The results of the keyframe extractions for these groups are also shown in Tables 4.7 and 4.8. Entropy in all reactions, then, appeared to be both measurable, at least observable, and correlated to the calculated entropy values. That is to say, MID2b reactions were more entropic than the reactions of MID2a as is the relationship between the calculated entropy scores (see Table 4.1) and MID1 reactions showed similar behaviors, closer in value to each other than the MID2 set.

Caution is necessary in deriving results from the videotaped reactions. Upon reflection, it occurred to me that, at least to some degree, the observed activities could result from group dynamics between friends and personalities. The first group of girls consisted of three best friends. The girls in the second group were all in the same class at school. The third and fourth groups of girls knew each other only by weekly contact at Girl Scout meetings and by acquaintance through my daughter. Higher observable activity levels were observed in the groups in which member familiarities were higher. This does not necessarily negate the confirmatory utility of the taped observations; it does, perhaps, raise interesting questions for future research. This study does not examine
or evaluate types of reactions to video nor the long term effects of individuals or the group regarding personality types and viewing materials.

<table>
<thead>
<tr>
<th>MID1a</th>
<th>MID1b</th>
<th>MID2a</th>
<th>MID2b</th>
</tr>
</thead>
<tbody>
<tr>
<td>happy</td>
<td>happy</td>
<td>boring</td>
<td>surprising</td>
</tr>
<tr>
<td>It was cool.</td>
<td>for younger children</td>
<td>bored</td>
<td>my favorite show</td>
</tr>
<tr>
<td>I liked it.</td>
<td>it was cute</td>
<td>It's just painting.</td>
<td>don't like it</td>
</tr>
<tr>
<td>It was okay.</td>
<td>I liked it</td>
<td>I really like painting so I really liked it.</td>
<td>a little kid’s show</td>
</tr>
<tr>
<td>It was interesting.</td>
<td>It was kind of funny.</td>
<td>I felt it was a really beautiful painting.</td>
<td>fun</td>
</tr>
<tr>
<td></td>
<td>It was kind of a little boring.</td>
<td>kind of boring</td>
<td>it was good</td>
</tr>
<tr>
<td></td>
<td></td>
<td>good if you like painting</td>
<td>not boring</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pretty good</td>
<td>interesting</td>
</tr>
<tr>
<td></td>
<td></td>
<td>kind of good</td>
<td>happy</td>
</tr>
</tbody>
</table>

Table 4.7: Numbers of keyframes extracted from Videotaped Interviews at Sensitivity Levels 20 and 50 with Virage® Video Logger

Figure 4.9: Comments about the MIDs as recorded during interviews when asked “How did you feel about the video?”
<table>
<thead>
<tr>
<th></th>
<th># of keyframes extracted at Sensitivity Level 20 excluding glitches in the data stream</th>
<th># of keyframes extracted at Sensitivity Level 50 excluding glitches in the data stream</th>
</tr>
</thead>
<tbody>
<tr>
<td>MID1a I</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>MID1a II</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>MID1b I</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>MID1b II</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>MID2a I</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>MID2a II</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>MID2b I</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>MID2b II</td>
<td>4</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 4.8: Numbers of keyframes extracted from Videotaped Interviews at Sensitivity Levels 20 and 50 excluding keyframes representing glitches in the data stream with Virage® Video Logger

I can speculate on several reasons why the interviews did not show more, that is, provide more insight into the children’s perceptions of the form complexity of the videos. The reasoning behind the experimental construct was to bring the children into my home where they might be more comfortable on my couch in a familiar environment. (These children are all friends of my daughter.) Familiarity may have had an adverse, or dampening, affect on the interview process. Children may have responded to my questions with words that they thought I might expect to hear. After all, I invited them into my home and showed them videos that I had chosen for them. They may have been trying to spare my feelings by not telling me certain videos were disliked. Or perhaps it is simpler than that. Their words actually were a reflection of their true perceptions as is indicated with the comparative judgments scores and perhaps nothing additional needed to be said. After all, their interviews do not run contrary to the other results, they simply do not present more insight.
Limitations With Virage® Video Logger

Several of the formulae used to calculate CEM involve the use of auditory material in the MIDs. The Virage® Video Logger is capable of logging only temporal and visual information, and so the audial information is lost. The Virage measurements should only be used as a tool of automatic extraction software when compared to CEM and PEM since a significant component of moving image documents is not yet detectable with the software. The software works at the micro level for detecting significant changes in the data stream. Often, keyframes are extracted at times when the viewer does not detect a significant change, as in Appendix E keyframes 39:12 to 39:17. The opposite constraint also occurs, where the viewer detects a significant change in data content or form but the software does not. Particularly, I was surprised by the number of keyframes extracted from MID2a. MID2a scored lower measurements for both CEM and PEM. It also had the fewest keyframes extracted, though the difference between it and the other MIDs was not as large as with CEM. Some of the children gave MID2a PEM values that were not largely different from the values given to MID2b (see Table 4.3). Viewers g, i, and j, for example, scored MID2a/MID2b 0.500/0.633, 0.717/0.746, and 0.575/0.642 despite the majority of the viewers scoring MID2a significantly lower than MID2b. Perhaps this is an indication, as the keyframe extraction suggests (Appendix D) that the viewer is perceiving what she is not necessarily aware of seeing.

With due regard to the limitations of a small sample of convenience and to the role of topical content, we can say that there is a demonstrable correlation between the calculated and perceived entropies. Therefore, we can accept the hypothesis that
mechanically CEM will be sufficiently similar to PEM made by children so that they can be used as useful and predictive elements of representations of children’s videos.
CHAPTER 5

IMPLICATIONS FOR THE FIELD OF INFORMATION SCIENCE

A grasshopper walks into a bar and asks for a drink. The bartender says, “You know, we have a drink named after you.” And the grasshopper says, “You have a drink named Bob?”

It’s funny, because it’s surprising, unpredicted, and it sways from established societal grammars. As long as one has some a priori knowledge of both a grasshopper (a winged orthopteran insect with hind legs adapted for jumping) and a grasshopper (3/4 oz green creme de menthe, 3/4 oz white creme de cacao, and 3/4 oz light cream), one understands the joke. “There are more than one hundred elements [to comedy], but the most important is the element of surprise. Boo!” (Idle, 1999, p. 122)

One has moved from the familiar to the unfamiliar with the introductory sentence “A grasshopper walks into a bar and asks for a drink.” Remove grasshopper from the sentence and add x, where x equals any possible passerby of the said drinking facility. Many North American adults are probably familiar with the joke lead in “An x walks into a bar…” and upon hearing it, prepares himself or herself to receive a humorous statement within the next few minutes. Despite the anticipation of humor, the recipient laughs—or groans, as it is with less sophisticated humor—and files it in his or her knowledge store for easy retrieval and use on another unsuspecting receptor.
Many parts of this joke present absurd notions of reality. Grasshoppers do not normally walk into bars, and if perchance one does—though it would likely be more of a hop—it would be impossible for it to order a drink, and even if it could order a drink, it would be impossible for it to consume the entire beverage and live. It seems even more absurd that a bartender (assumed to be a human creature) would speak to a grasshopper that just wandered into his establishment demanding a drink and entertain the notion that perhaps the grasshopper may already be aware of the fact that there is a drink named after him. To complete the absurdity is the grasshopper’s reply: “You have a drink named Bob?” Not only can this grasshopper speak, but it also has a name common to human pub goers. The receptor laughs not only at the absurdity that has been built in three short sentences, but also at the dramatic irony the grasshopper has suffered for not possessing the a priori knowledge of the potent libation, a grasshopper.

So what? Useful information, or communication, is the as yet unknown—but one can be prepared for the unknown within the structures of what is known. Good hunting—which Wilson (1968) asserts we must do, because no information retrieval system will be perfectly designed for each user and each use—hinges on discovering the useful unknown: sometimes detecting the slight difference from the norm; sometimes knowing the pattern (‘an x walks into a bar’) that will put one in the right place. As with hunting, the joke format tells us to expect the unexpected. Paul Rezendez, a wildlife photographer, asserts, “If you spend time learning about the animal and its ways, you may be able to find the next track without looking…. Tracking an animal…brings you closer to it in perception” (Rezendez, 1992, p. 7). Likewise, Wayne Gretzky claims to try to skate to where the puck is going to be by making predictions about the unknown. Thus, we might
say that humor, as a structural method of using entropy, could serve as a probe or
touchstone for thinking about information seeking environments.

Entropy and Prototyping in the Brain

Entropy is high when it approaches a middle, as in a value of 0.5 on a scale of
zero to one (see Figure 5.1). Conversely, when one element of a message system is at the
extreme high or extreme low, the entropy measure is low, as in most of the measures for
MID2a, (see Table 4.1). The painter in this MID, Bob Ross, speaks for nearly the entire
10 minute segment and he is the only character who verbalizes during the segment.
Verbal Time Entropy (HVT) is calculated by comparing the total verbalization time of
each character with the total verbalization time of all the characters. This verbalization
time is an example of an element at an extreme high, which—plugged into the formula—
makes the HVT measure low, in this case zero. In the same MID, Character Appearance
Entropy (HCA) is also zero, because the element (the number of times characters enter or
exit the frame) is at the extreme low, with zero entrances and exits. This is similar to the
concept of prototyping in the brain (B. C. O’Connor, personal communication, February
2000) where the farther away from the middle value an item falls, that harder it is to
justify that item as part of the group. Conversely, just because something is not just like
the prototype does not mean it cannot be a member of the class (Smith & Medin, 1981).
Consider the example of birds. Most people will describe *bird* as a small, winged creature that flies, lays eggs, has a beak and feathers, and makes lovely sounds. This normal description of *bird* may trigger images of a robin, or blue jay, or oriole, but it will not apply equally to all members of the group (Roth & Frisby, 1986). Take other birds that do not fit this middle description: penguin, or emu, or chicken. These are still birds despite not encapsulating the entire original attributes of birdness. Take other creatures that fit only some attributes of birdness, like mosquito (lays eggs, flies, makes sound), or platypus (lays eggs, has a beak), or flying squirrel. Though these creatures are surely not birds, they do belong to the group based on certain attributes. Could the group be stretched further to include airplane? The farther one deviates from the normal, or middle—or becomes “ill-defined” or “fuzzy” (Roth & Frisby, 1986, p. 29)—the more difficult it is to include the item in the group, though it still is.

This prototyping in the brain seems to hold also for assigning entropy values to moving image documents. MID2a, *The Joy of Painting*, and MID1a, *Wild Discovery*,

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Figure 5.1: Entropy is high as it approaches the middle.
have lower calculated entropy scores than the documents that were created for child audiences, though the perceived entropy values, given by the child viewers themselves, indicate that even though MID1a and MID2a do receive lower entropy values, they are not excluded from the group of MIDs that are interesting to children. The calculable entropy measure, then, acts as a guideline for interpreting what could be the normal entropy value to children as their perceptions hold similar relationships to the calculated measurements.

The knack of joke telling is one of eliciting a willing suspension of receptor disbelief of what may be normal through audial and temporal signals. The farther one moves away from the normal set of properties of an object, as in one’s notion of the degree of *birdness*—where an airplane possesses some birdness when it flies, as does a gecko when it lays eggs—the more difficult it is to believe, or to accept as part of the group even though it still belongs in the group. The amount of space between airplane and blue jay, for example, on the scale of birdness is unknown except for the fact that it is greater than the space between blue jay and owl and smaller than the space between blue jay and automobile. The farther an object moves away from normal along the scale of birdness, the more difficult it becomes to form relationships between the object and what is normal. That is to say that the relationships between an object within the normal range and an object outside the normal range are more unpredictable, or more entropic. Because the grasshopper’s response fell outside of what regular people may consider the normal set of properties defining a grasshopper’s behaviors and capabilities, entropy was high. In fact, information is high under maximum unpredictability.
The transmission of information implies order, as in the transmission of a joke where the communicator guides the receptor through a sequence of events. It seems contradictory, then, that the chaos, or disorder, of the unpredictableness, by which the joke became funny, produces an increased amount of information available to the receptor for deciphering. So, that which generates the most disorder is itself rendering order. This “Babylonian muddle” (Arnheim, 1971, p. 15) is obviously a result of misdefined and misused terms (Hayes, 1994). What one generally refers to as order, in the context of information, is more properly called structure. The structure of the joke, then, is what leads to the maximum disorder or unpredictability of the message, eliciting a humorous response from the receptor.

“Ask me the secret of comedy.”

“What is the secret of—“

“Timing.”

Even as far back as the first time this joke was told, people were aware of the importance of structure in the construction of humor, at least the temporal dimension (Idle, 1999).

There are at least two possible occurrences of maximum information, or high entropy, with regard to humorous events: the anticipated entropy and the unexpected entropy. In the joke, one recognizes both. There is the recognition of the joke structure—“An x walks into a bar”—that precedes the anticipated punch line; and there is the actual punch line and other unexpected content and perhaps unexpected temporal structure in the amount of message that passes between the introduction and the conclusion. As with MIDs, the structure of a joke cannot overpower the content. If one leaves the joke behind
and considers assorted MIDs, anticipated and unexpected structure seems very common. One knows that one of the Three Stooges will inevitably be poked in the eye or bopped with a ladle to the head. The viewer even anticipates that it will probably be Curly. Yet for fifty years, viewers have been watching, anticipating comedy, laughing, and waiting for reruns. Structure of the medium keeps the content fresh. Perhaps the audial component of absurd sound affects—the sound of coconuts being knocked together as two heads collide, or a zipper opening to accompany the clam spitting in Curly’s face—is what gives the Three Stooges their entropic edge. Unexpected entropy occurs when one watches an MID that may not be categorized as a comedy, but that interrupts the structure of the message with a high entropy situation. Of course, unexpected entropy in real life—not in MIDs—might result in the elicitation of emotions other than humor.

I can never forget when I watched my Tenth Grade Religion teacher walk out of school, as he did every day, and walk toward his car. Just as he reached the edge of the parking lot, he slipped on a patch of ice and fell. I laughed. The structure of the message was interrupted with a sort of entropic glitch and created a humorous situation. It was obvious that my teacher, however, was feeling an array of emotions not even related to humor.

If humor is so simply equated to entropy, then it could also be paired with other perceptions of structure for the purpose of employing entropy in representations of documents. When someone laughs at you, you may be angered, or startled, or dumbfounded by the entropic glitch. If the amount of entropy equals the amount of information in a message, than this information about an MID, or a joke, or any communication could be used to enrich representations (see Figure 5.2 for a model of
successful retrieval from normal representations) about practically any communication; the anticipated or unexpected element being represented by Hayes’ $r$. Hayes’ $r$ represents known codes and, thus, the decodable unknown. If Curly began speaking Greek out of context and the other Stooges did not react, it would not be funny; it would be confusing, and perhaps annoying.
Figure 5.2: Ideal Situation of Successful Retrieval of Documents from Representations of Children’s Media, adapted from O’Connor 1996

Based on Blair’s notion of subject indeterminacy (1986), document representations have to have the same attributes as the documents being sought and they
have to be in the same code. Given typical topic based system side representations, this model works for the situation where the child says, “I need some books about horses.” What would the representations have to contain for the situation when the child says, “I want to read something that other kids enjoyed reading”? 

Entropy Representations in Other Media for Children

Consider picture books, which have both form attributes and content attributes. Form attributes may be said to comprise the syntax of the book; content attributes comprise the semantics. Entropy describes the rate of information or the degree of randomness in a message, so describing syntactic attributes of a book is the goal of implementing a calculated entropy measure (CEM). That is not to say that the semantics of the book are not important to the reader, for the rate of information of any document does not overpower the topic; however, the semantic aspects of communication are irrelevant to the engineering aspects (Shannon & Weaver, 1964). Because information theory relates not so much to what one says but to what one could say, one message of pure nonsense and one message loaded with meaning can be exactly equivalent. This is the case for Dr. Seuss’ literature. He often used words that he invented in order to tell a story, and despite his nonsensical vocabularies, the information in his books is as attractive to readers—possibly more attractive—than books containing all familiar words. Perhaps the attractiveness of his books is, in part, due to the ways he engineered his unordinary syntaxes.

If one could apply the entropy equation to the form attributes of books, predictions of children’s perceptions of books might also be added to representations of those books. To do this, one must separate syntactic attributes from semantic attributes.
Some semantic attributes may be the use of illustrations to carry the narrative, the use of original words, the use of foreign language words, and the use of literary devices like surprise ending or onomatopoeia. Essentially, semantic attributes describe topical content. Syntactic attributes describe the information, such as the arrangement and organization of visuals, mechanical or working parts, the degree of randomness of visuals used to carry the narrative, or the number of colors used per illustration. Several extra-topical attributes can be described if one focuses on the structure or the syntax of a picture book.

I returned to the status of naïve scientist and devised an exploratory examination into representing syntactic entropy of children’s books. Six syntactic attributes are proposed in Figure 5.3 with the formulae used to calculate the syntactic complexity in children’s books, that is, the degree of randomness of extra-topical elements. These formulae were applied to the five picture books (some pages of which are shown in Figure 5.4) by award winning authors.
### Mechanical Components Entropy (HMC)

The degree of randomness of working or mechanical components in a book:

\[
\text{H}_{\text{mech}} = \log_2 \frac{n_{\text{mech}}}{n_{\text{pages}}}
\]

where

- \(n_{\text{mech}}\) = total number of working or mechanical parts
- \(n_{\text{pages}}\) = total number of pages

### Word Incidence Entropy (HWI)

The degree of randomness of the appearance of individual words in a book:

\[
\text{H}_{\text{words}} = \sum_{i=1}^{k} \log_2 \frac{n_{\text{words}_i}}{t_{\text{words}_i}}
\]

where

- \(n_{\text{words}_i}\) = total number of words appearing on the \(i\)th page
- \(t_{\text{words}_i}\) = total number of words
- \(k\) = number of pages with text

### Text Appearance Entropy (HTA)

The degree of randomness of the appearance of text on a page:

\[
\text{H}_{\text{block}} = \log_2 \frac{n_{\text{block}}}{n_{\text{page}}}
\]

where

- \(n_{\text{block}}\) = total number of blocks of text appearing in the book
- \(n_{\text{page}}\) = total number of pages

### Character Appearance Entropy (HCA)

The degree of randomness of appearance of characters appearing in illustrations throughout the book:

\[
\text{H}_{\text{char}} = \sum_{i=1}^{k} \log_2 \frac{n_{\text{char}_i}}{t_{\text{char}_i}}
\]

where

- \(n_{\text{char}_i}\) = total number of characters appearing on the \(i\)th page
- \(t_{\text{char}_i}\) = total number of characters
- \(k\) = number of characters

### Character Incidence Entropy (HCI)

The degree of randomness of the occurrence of the main character in the book:

\[
\text{H}_{\text{mchar}} = \sum_{i=1}^{k} \log_2 \frac{n_{\text{mchar}_i}}{n_{\text{pages}}}
\]

where

- \(n_{\text{mchar}_i}\) = number of pages featuring the main character
- \(n_{\text{pages}}\) = total number of pages

### Non-text Dependence Entropy (HNT)

The degree of randomness of the use of only visuals to carry the narrative:

\[
\text{H}_{\text{nontext}} = \log_2 \frac{n_{\text{nontext}}}{n_{\text{pages}}}
\]

where

- \(n_{\text{nontext}}\) = total number of pages containing text of the narrative
- \(n_{\text{pages}}\) = total number of pages

---

**Figure 5.3:** Suggested Entropy Formulae for Calculating Syntactic Complexity in Children’s Books
<table>
<thead>
<tr>
<th>Author</th>
<th>Title</th>
<th>Text Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bunting, Eve</td>
<td>Smoky Night</td>
<td>words in standard paragraphic form</td>
</tr>
<tr>
<td>Burton, Virginia Lee</td>
<td>Mike Mulligan and his Steam Shovel</td>
<td>pictures and words both as graphical elements</td>
</tr>
<tr>
<td>Lyon, George Ella</td>
<td>Book</td>
<td>words embedded in illustrations, separate from actual text</td>
</tr>
<tr>
<td>Munsch, Robert</td>
<td>Stephanie’s Ponytail</td>
<td>words in paragraphic form and an illustration embedded in the block of text</td>
</tr>
<tr>
<td>Seuss, Dr.</td>
<td>There’s a Wocket in My Pocket</td>
<td>original words and characters</td>
</tr>
</tbody>
</table>

Figure 5.4: Page samples from children’s books by award winning authors
Mechanical Components Entropy (HMC) measures the degree of randomness of working or mechanical parts, such as pop-up features and moveable parts. None of the books measured here has mechanical parts, but many books do, as in *The Twelve Days of Christmas* by Robert Sabuda and *Doorbell* by Jan Pienkowski. Word Incidence Entropy (HWI) measures the degree of randomness of the appearance of individual words in a book. Figure 5.4 shows a comparison between books with few words per page in Seuss and books with many words per page in Munsch. Text Appearance Entropy (HTA) measures the degree of randomness of the appearance of text on a page. Figure 5.4 shows the variation of the design of blocks of text with single blocks of text in Bunting and multiple blocks in Burton. Character Appearance Entropy (HCA) measures the degree of randomness of appearance of characters in illustrations throughout the book. The figure shows Bunting has four characters on this particular page and Lyon has two. Character Incidence Entropy (HCI) measures the degree of randomness of the occurrence of the main character. In Seuss one sees the main character appearing on both of the facing pages whereas the main character in Bunting is not featured on these particular pages. Non-text Dependence Entropy (HNT) measures the degree of randomness of the use of only visuals to carry the narrative. In Lyon, mostly visuals are used to tell the story. There is very little text apart from the words that are part of illustrations.

The CEMs are shown in Table 5.1. The results of these calculations, following the same format as with the MIDs for calculating entropy, show that the order from most entropic to least entropic information is Munsch, Bunting, Lyon, Seuss, Burton. Individual element values range from 0 (for Mechanical Components Entropy in all books) to 0.577 (for Text Appearance Entropy in Seuss.) Some books measured high for
some attributes, showing that the information they held was high with regard to text appearance or non-text dependence, despite their total values measuring lower than the other books.

<table>
<thead>
<tr>
<th></th>
<th>Bunting</th>
<th>Burton</th>
<th>Lyon</th>
<th>Munsch</th>
<th>Seuss</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMC</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>HWI</td>
<td>0.262</td>
<td>0.136</td>
<td>0.306</td>
<td>0.328</td>
<td>0.185</td>
</tr>
<tr>
<td>HTA</td>
<td>0.500</td>
<td>0.034</td>
<td>0.410</td>
<td>0.477</td>
<td>0.577</td>
</tr>
<tr>
<td>HCA</td>
<td>0.137</td>
<td>0.107</td>
<td>0.150</td>
<td>0.164</td>
<td>0.166</td>
</tr>
<tr>
<td>HCI</td>
<td>0.531</td>
<td>0.489</td>
<td>0.482</td>
<td>0.517</td>
<td>0.249</td>
</tr>
<tr>
<td>HNT</td>
<td>0.500</td>
<td>0.322</td>
<td>0.380</td>
<td>0.500</td>
<td>0.415</td>
</tr>
<tr>
<td></td>
<td>0.322</td>
<td>0.181</td>
<td>0.288</td>
<td>0.331</td>
<td>0.265</td>
</tr>
</tbody>
</table>

Table 5.1: Syntactic Complexity (CEM) for 5 Children’s Books

The purpose of assigning CEM to documents for children is that CEM can stand for the perceived entropy measure (PEM); this has been demonstrated for MIDs, but can we say the same relationship could be true for books? I asked 25% of the children from the original study to rank the five books in order of their favorite to least favorite by assigning the numeral 1 to the most favorite, 2 to the next favorite, and so on up to 5, as demonstrated by Dunn-Rankin (P. Dunn-Rankin, personal communication, October 2000). Table 5.2 shows the results of their rankings.

<table>
<thead>
<tr>
<th></th>
<th>Bunting</th>
<th>Burton</th>
<th>Lyon</th>
<th>Munsch</th>
<th>Seuss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child A</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Child B</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Child C</td>
<td>1</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>total</td>
<td>7</td>
<td>11</td>
<td>12</td>
<td>5</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 5.2: Child Rankings for Five Picture Books

The book with the lowest ranking total value is the favorite book of the group. Munsch had the lowest value and Bunting had the second lowest value. The children
chose Munsch as their favorite and Bunting as their second favorite. These findings support the same relationships as the CEM for these two books. At least with this small sample group, CEM can generally be calibrated to PEM for picture books. The children provided topical reasons for ranking their first book. However, semantic interest is probably enhanced by syntactic information, even if the reader is unaware of the structure information. It seems likely that content attributes are more likely to impact children than adults since children in this age group are just learning to understand the structures of information and they are less likely to understand abstract characteristics of document form (Kuhlthau, 1988) (see Figure 5.9). A larger sample would be necessary to validate the relationship between CEM and PEM for picture books, but values suggest this small sample group hints at the possibility of a trend for the age group, and at the possibility of adding one more color to the representation palette of children’s books.

Could the same relationships between CEM and PEM hold for other media for children, such as images, chapter books, audio recordings, software, or websites? The relationships between PEM and CEM of the tested media suggest that such a relationship might be established in other media. Different media would require entropy formulae specific to the structural uniqueness of each. Still image documents, for example, could be represented by Color Incidence Entropy (HCO), the degree of randomness of the number of colors occurring in the image. When the image is digitized, the number of colors it contains can be counted in imaging software, such as Paint Shop Pro® by Jasc Software. Figure 5.5 describes a suggested formula for calculating form complexity in one structural attribute of still image documents. Calculating entropy of other image
elements for the purpose of content based mechanical image retrieval has also been accomplished (see Zachary, 2000).

| Color Incidence Entropy (HCO) | the degree of randomness of the number of colors in the image |  \( \frac{n_{\text{color}_i} \cdot \log_2 n_{\text{color}_i}}{n_{\text{pixels}}} \) | where \( n_{\text{color}_i} = \text{total number of colors in the image} \) and \( n_{\text{pixels}} = \text{total number of pixels comprising the image} \) |

Figure 5.5: Suggested Entropy Formula for Image Documents for Children

The image in Figure 5.6 has a CEM for HCO of 0.524. This was calculated using the number of colors (80,482) found in the digitized version of this image and the number of pixels (187,500) that comprise the digital image. For comparison, the CEM of this attribute was calculated (0.515) for a second image, shown in Figure 5.7, with the number of colors 33,771 and the number of pixels equaling 120,000.

Figure 5.6: Image used for CEM of HCO captured by Brian Bagatto, December 2000
A sepia toned image digitized with true color information is likely to have a lower rate of information for this attribute, as shown in Figure 5.8, since there is a less surprise in the structure of the message. Having children individually grouping images, or sorting images, into piles of categories that they contrive and then having them describe their categorization scheme may be one way to measure PEM for images (B. O’Connor, personal communication, April 2001).
Entropy Representations and Developmental Stages

The ways in which children perceive documents are different from the ways adults perceive the same documents because children have different developmental and cognitive abilities than adults. Adult representations of children’s documents may not represent children’s perceptions of the same documents. Since reality is subjective, because “each person personally contemplates the stream of events upon which he or she is so swiftly borne” (Kelly, 1955), it is improbable, or at least requires additional effort, that one group or one person can say how another categorizes documents in ways that are meaningful and personal. However, being aware of information needs specific to developmental stages allows one to make predictions about what might be meaningful for a particular age group. Even representations for children of different ages should reflect their different developmental stages. Kuhlthau (1988) synchronized the stages of cognitive development in children of several psychologists to discuss developmental information needs of children, as described in Figure 5.9. Children of ages 7 to 10, in middle childhood, have information needs that are distinct from the needs of younger children (learning to read and accepting and following rules) and from the needs of older children (evaluating information and thinking both critically and abstractly.) Numerical representations of entropy in materials specific to stages of development may increase relevance of retrieved documents for a particular child since the numerical representation, say 0.235 or 0.544, provide a sort of rating system for judging the rate of information, or the complexity of the information, or the structure of the information of any document and the child can choose materials based on an amount of desired complexity. If the information needs of children, age 7 to 10, include learning how information is
organized, then knowledge about the structure of information in a document is extremely useful. Such a mechanism for richer representation of children’s documents could help strengthen searcher knowledge and insight of the desired document in a system of categories.

<table>
<thead>
<tr>
<th>Stage of Development</th>
<th>Characteristics of Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piaget</td>
<td>Concrete Operational</td>
</tr>
<tr>
<td></td>
<td>• performs mental tasks on a concrete level</td>
</tr>
<tr>
<td></td>
<td>• not commonly capable of abstract thinking</td>
</tr>
<tr>
<td></td>
<td>• begins to make rational judgements about concrete or observable phenomena.</td>
</tr>
<tr>
<td>Erikson</td>
<td>Industry versus Inferiority</td>
</tr>
<tr>
<td></td>
<td>• develops a capacity for industry while avoiding an excessive sense of inferiority</td>
</tr>
<tr>
<td>Kohlberg</td>
<td>Conventional Morality</td>
</tr>
<tr>
<td></td>
<td>• performs good acts and maintains social order</td>
</tr>
<tr>
<td></td>
<td>• not directed by a fully developed conscience</td>
</tr>
<tr>
<td>Kuhlthau’s Information Needs</td>
<td>• expand general information base</td>
</tr>
<tr>
<td></td>
<td>• use developing communication</td>
</tr>
<tr>
<td></td>
<td>• needs the opportunity to ask questions and to explain things in order to mentally manipulate information capabilities</td>
</tr>
<tr>
<td></td>
<td>• begin to understand the organization of information</td>
</tr>
<tr>
<td></td>
<td>• learns to plan</td>
</tr>
</tbody>
</table>

Figure 5.9: Stages of Cognitive Development of Several Psychologists paralleled with Information Needs of 7 to 10 Year Old Children; adapted from Kuhlthau, 1988.

From this notion, a model emerges that is responsive to the situation in which the child says, “I want to read something that other kids enjoyed reading.” Certainly, no child is going to want or use entropy measures if he or she just wants any books about horses. However, once affective components or evaluative components come into play, CEM is
important. The numerical representations of entropy alone are probably meaningless to the children they are intended to guide; however, an interface between the documents and the children could include a comparative judgement—much like the line graphs used to quantify perceived entropy in child viewers (see Figure 4.6)—that shows the child how exciting, for example, other children, or the system’s prediction) found a certain document. Figure 5.10 is a model demonstrating how successful retrieval could result from including entropy measures.

Figure 5.10: Model of Representation Enriched with Entropy Values

The basic idea behind implementing the entropy measure in this form for representations is to help personalize the representation by including a relevance factor,
such as Hayes’ $r$. The notion of personalizing representations is not a new one. Book reviews, for example, guide adults to select items for specific children. Reviews are not likely to help the child information seeker without having to wade through the words of the adult who wrote the review. Reviews written by children in the same cognitive and developmental group as the information seeker would provide more useful information. A system that supports an interface like the model in Figure 5.10 might also be able to display reviews by other children who have used the item and to include a place to accept continuous input from the readers to add data to the line graphs. The system could prompt, “If you read this book (or watched this video) how do you rate it?” The child could choose to position the marker using the mouse to slide the green dot to any place along the continuum from less exciting to more exciting and her input would be fed back into the measure. This idea is similar to the system used to rate items for sale on Amazon.com (see Figure 5.11). The system even ranks how helpful customers have found the reviews. Child searchers should not be limited, however, to average representations constructed with taking the mean of all responses. Perhaps each child, by positioning the dot, could prompt the system to construct a personalized representation specifically for that child and provide individualized search results, while adding his or her data to the pool. Cooper (1983) speculates that there may be ways of using an entropy-weighted design to “include the possibility of probabilistic request modification in response to user judgements about output items” (p. 38).
Figure 5.11: Ranking System and Reviews by Users Implemented by Amazon.com

The question arises, then, if such a representation device is effective when implemented in representations of documents for children ages 7 to 10 years, can the same calibration of CEM to PEM be applied to documents of other age groups with different information needs?

Entropy as Predictor of Document Relevance

The implementation of an entropy representation may increase precision and recall not only in a retrieval system but also on the World Wide Web. With maximum precision and recall applied to a particular search, a system should locate all of the
documents relevant to the information need of a searcher. Problems exist, though, in the
degree of a searcher’s articulation of the need and with the inability of most systems to
understand what the searcher really wants (Borgman, 1996). A system could, for
example, point a searcher to any document about a topic, or by an author, and with an
information rate of 0.323. Perhaps this notion simply provides more specificity for the
search, since entropy could represent the perceptions of the majority of a particular
cognitive, developmental group toward the information of a particular document. A
document with an entropy value of 0.013, created for adult groups, might tell a child or
adolescent searcher that the information is more boring than, say, a document with an
entropy value of 0.436, since the higher entropy score represents greater surprise—
possibly greater excitement—in the structure of the message.

Documents have structure, though structure among document sets differs. At the
very least, the structure of information can be observable. A moving image document
usually has temporal, audial, and visual information; a picture book has visual and textual
information; an image has many elements of visual information. Whether or not one is
aware of the structure of the information, one will be inclined to decode the message.
Now consider the World Wide Web—a wilderness, a bewildering entity of inconsistent
predictability of relevance. Search engines supply the illusion of structure of the Web,
despite its actual structurelessness, or abstract structure, manifested through associations
of hyperlinks (Palmquist & Kim, 2000). For some, this is what makes the Web so
appealing and exciting. One calculated entropy measure applied to the entire network
would probably be quite high. A perceived entropy measure of many users is likely to be
even higher. Collections with greater information—higher entropy—are environments
with greater browseability (O’Connor, 1988), as was the case with the Big Red Dot collection for first graders described in Chapter 1. Search engines attempt to rank hits to a search request to try to reduce information by imposing some mechanically conjured algorithmic order that might be meaningful to the searcher. Some leave the searcher berrypicking (Bates, 1989) through layers and layers of websites before finding what might be an answer to the original question, but such is the nature of evolving ideas…and evolving website connections. Ranking search hits based on mechanical calculations of relationships between words in a document and words in a query and listing most relevant first and second most relevant next, and so on, seems absurd since relevance is chosen by the searcher and not by the search tool. Cooper (1983) asserts that retrieval systems could present weighted ranking of search results calculated with the maximum entropy principle in order to predict precision of the results. The search engine Google ranks pages with a measure of individual page importance based on the number of pages that link to it. This value plus computational evaluation of matching search terms is what retrieves relevant pages for the searcher. Google comes close to providing structural information in hits retrieved, but instead of relevance judgements, search engines might employ entropy measures of individual websites: how the information on a single point in the wasteland of information is structured. A low entropy score may seem inviting to some who have been lost in the confusion. Sometimes, boring is better. With the Web, we see only a window on a data stream with no sense of length, width, or depth. Given this complex nature of documents and the people searching for them, relevance cannot be predicted with any certainty by the system (Robertson, Maron, & Cooper, 1982), but
system administrators can provide stronger clues to document information, like entropy, to help the user predict relevance for himself or herself.

Recall and relevance seem to be applied to the literal application of entropy ratings to information wells. Recall and relevance, with regard to the individual’s ability to remember meaningful ideas may also be linked to high and low entropy measures. Lower entropy should generate greater recall of information. When the rate of information is low there is less information to recall, and when the rate of information is high there is more information to recall about the message after it was first received. Less information to recall could also mean the receptor has less information to complete, or to assimilate. This is related to McLuhan’s (1964) notion of hot and cold media, where hot media are those media that require little audience completion, and cold media are those that require much audience completion. One interpretation of hot and cold media is shown in Figure 5.12. The willing level of involvement on the part of the receptor will likely influence the choice of media for receiving a message, much the same as high entropy values assigned to a message could either attract or deter the same person.
The willing level of receptor involvement in the decoding of the message could be linked to his or her intrinsic and extrinsic motivation in participation of the message. Most children love to be introduced to a new book, especially when a parent is reading and it has some special place in the bedtime routine. Level of involvement was probably extrinsically initiated outside the receptor—the child—with some other extrinsic forces, like the soothing routine with a bedtime story. But what motivates the child to choose the same book the next night and the next and the next until the parent—and the child—has the book memorized and can do the proper character voices even while paying attention the local weather report playing on the television in the next room? The book has been read so many times that the child knows all the places he or she is supposed to be
surprised. The rate of information has not changed in the book, but the child has. The information—with Hayes’ $r$ representing the intrinsic relevance of the book to the child—has become predictable, making entropy, for this child, low. It is possible that this intrinsically weighted interest in the message keeps children asking for the same low entropy story event night after night, and the same could be true of low entropy television programs like *Mr. Rogers’ Neighborhood*, which has been on the air for 25 years.

Less information is less surprise in a message, which requires less decoding time for the receptor to understand the message. When the punch line comes in the wrong place in the structure of the joke, it is not funny. A simply structured message requires less decoding time for the receiver to arrive at the semantic message. Messages with complex information—whether the message is a moving image document, a book, a still image, or a joke—involves greater commitment from the receptor. Augst and O’Connor’s study (1999) showed that the “exciting” video had a higher entropy but cross-country coaches preferred the lower entropy video because they could easily use it to point out strategies to their runners. Some prefer the simpler message from the hot medium where one does not have to be deeply committed to sorting out the information, suffering the embarrassment of being—after hearing a joke—always the last one to say, “Ah! I get it!”

The notion of alternative representation schemes for different user groups is not a new one. Recall the descriptions from tvguide.com of the MIDs used in this study. MID1a is assigned the rating “TV G.” MID1b and MID2b, under the same representation scheme, are rated “TV Y” (see Figures 3.2, 3.3, and 3.5). Richard Kahlenberg, a founding archivist of the American Film Institute and writer for the *L.A. Times* points out that millions of dollars have been spent on finding adequate representation for television
programming. The results employ only a few letters of the alphabet (Y and G being two of them). What about all the other letters? Could more letters be used in order to improve representations of television programming? (R. Kahlenberg, personal communication, January 2000).

Information seeking and retrieval systems are fundamentally representation systems. Informal, personal systems—friends, chats with a good reference librarian—have used both topical and extratopical document attributes, together with user appropriate terms. Formal bibliographic systems developed in a time of manual representation, per force, emphasized system side representation of topical attributes. As mechanisms for both document analysis and user feedback become more available, we are able to represent and serve the user side more richly. Reviews, forwards, and acknowledgements, also, have presented extratopical information. Calculating entropy measures for all documents may not always put a useful document into the hand of every information seeking child, but information providing communities can now construct representations of documents that provide higher utility for information seekers by adding one more color to the representation palette. This study has shown, for a single medium—moving image documents—one way to increase the predictive power of representations for children.
APPENDIX A

COMPARATIVE JUDGMENTS QUESTIONNAIRE
Would you want to see the 1st video again?

Would you want to see the 2nd video again?
How exciting was the 1st video?

How exciting was the 2nd video?
How much do you like the 1st video?

How much do you like the 2nd video?
How funny was the 1st video?

How funny was the 2nd video?
How boring was the 1st video?

How boring was the 2nd video?
How surprising was the 1st video?

How surprising was the 2nd video?
APPENDIX B

KEYFRAMES SELECTED FROM MID1a BY VIRAGE® VIDEO LOGGER SET AT SENSITIVITY LEVEL 20
APPENDIX C

KEYFRAMES SELECTED FROM MID1b BY VIRAGE® VIDEO LOGGER SET AT SENSITIVITY LEVEL 20
APPENDIX D

KEYFRAMES SELECTED FROM MID2a BY VIRAGE® VIDEO LOGGER SET AT SENSITIVITY LEVEL 20
APPENDIX E

KEYFRAMES SELECTED FROM MID2b BY VIRAGE® VIDEO LOGGER SET AT SENSITIVITY LEVEL 20
APPENDIX F

KEYFRAMES SELECTED AT SENSITIVITY LEVELS 20 AND 50 WITH BY

VIRAGE® VIDEO LOGGER
MID1, Group 1

Group 1 watching MID1a Sensitivity Level 20

Group 1 watching MID1a Sensitivity Level 50

Group 1 watching MID1b Sensitivity Level 20
Group 1 watching MID1b Sensitivity Level 50

MID1, Group 2

Group 2 watching MID1a Sensitivity Level 20

Group 2 watching MID1a Sensitivity Level 50
Group 2 watching MID1b Sensitivity Level 20

Group 2 watching MID1b Sensitivity Level 50

MID2, Group 1

Group 1 watching MID2a Sensitivity Level 20
Group 1 watching MID2a Sensitivity Level 50

Group 1 watching MID2b Sensitivity Level 20

Group 1 watching MID2b Sensitivity Level 50

MID2, Group 2

Group 2 watching MID2a Sensitivity Level 20
Group 2 watching MID2a Sensitivity Level 50

Group 2 watching MID2b Sensitivity Level 20

Group 2 watching MID2b Sensitivity Level 50
APPENDIX G

LETTER OF APPROVAL FROM THE UNIVERSITY OF NORTH TEXAS

INSTITUTIONAL REVIEW BOARD
Jodi Keams  
913 Sierra Dr.  
Denton, TX 76209

RE: Human Subjects Application No. 00-221

Dear Ms. Keams,

On November 17, 2000, the University of North Texas Institutional Review Board conducted a full review of your proposed project titled "Calculated Versus Perceived Entrophy in Moving Image Documents." The University of North Texas IRB feels that with the submission of the requested changes the risks inherent in this research are minimal and the potential benefits to the subjects outweigh those risks. The submitted protocol is hereby approved for the use of human subjects on this project.

Enclosed is the consent document with stamped IRB approval. Please copy and use this form only for your study subjects.

U.S. Department of Health and Human Services regulations require that you submit annual and terminal progress reports to the UNT Institutional Review Board. Further, the UNT IRB must re-review this project annually and/or prior to any modifications you make in the approved project. Federal policy 21 CFR 56.109(e) stipulates that IRB approval is for one year only.

Please contact me if you wish to make changes or need additional information.

Sincerely,

[Signature]

Reeta Bushby  
Chair, Institutional Review Board

RB: sb
APPENDIX H

COMPARISONS BETWEEN IMPLEMENTATIONS OF SHANNON’S ENTROPY EQUATION USING THE MEAN FUNCTION AND THE SUMMATION FUNCTION
Chart of mean values

MID1a is 55.46% of MID1b
MID2a is 5.21% of MID2b

<table>
<thead>
<tr>
<th></th>
<th>MID1a</th>
<th>MID1b</th>
<th>MID2a</th>
<th>MID2b</th>
</tr>
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<tbody>
<tr>
<td>HST</td>
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<td>HSI</td>
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<tr>
<td>HVT</td>
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<td>0.48397</td>
<td>0</td>
<td>0.39984</td>
</tr>
<tr>
<td>HVI</td>
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<td>0.46107</td>
<td>0</td>
<td>0.40651</td>
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<td>HSC</td>
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<td>0.21360</td>
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<td>0.21695</td>
<td>0.39118</td>
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</table>

Chart of summation values

MID1a is 42.32% of MID1b
MID2a is 1.85% of MID2b

<table>
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<tr>
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<th>MID2a</th>
<th>MID2b</th>
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<td>1.0000</td>
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<tr>
<td>HVI</td>
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<td>0</td>
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<tr>
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<td>0.2136</td>
<td>0</td>
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<tr>
<td>HNV</td>
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<tr>
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<td>0.4604</td>
<td>1.0878</td>
<td>0.0191</td>
<td>1.0336</td>
</tr>
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</table>
REFERENCES


Burow-Flak, E. (1999). From Gutenberg to Gates: Literature and the transmission of the text from the early to the late age of print. Indiana: Valparaiso University, 

http://www.valpo.edu/home/faculty/bflak/gutenberg/index.html


